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TESIS DOCTORAL

Essays on market discipline, banking and regulation

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DEPARTAMENTO DE ECONOMÍA DE LA EMPRESA

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Doctoral Thesis

Essays on market discipline, banking and regulation

Matias Cabrera

supervised by
Dr. Margarita Samartín-Sáenz
Dr. Gerald P. Dwyer

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Doctor of Philosophy
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Madrid, Mayo 2016

Contents

Abstract

This Dissertation presents three studies on market discipline, implicit guarantees, sovereign risk and bank regulation. Chapter one analyzes whether larger banks are deemed as *Too Big to Save* by analyzing their stock returns' reaction to a set of announcements regarding governments' bailout capacity. In order to assess if there has been a risk transfer from banks to sovereigns (due to implicit guarantees), chapter two analyzes the reaction of sovereign bond spreads to downgrades on banks' *standalone ratings*. Finally, chapter three analyzes, from a theoretical perspective, the interaction between liquidity and capital requirements, and their effect on bank risk-taking.

Esta tesis presenta tres estudios sobre temas relacionados con la disciplina de mercado, seguros implícitos, riesgo soberano y regulación bancaria. El primer capítulo analiza si los bancos más grandes pueden ser considerados como *Demasiado Grandes para Salvar*. Pare ello se analiza la reacción de los rendimientos de las acciones de los bancos a un conjunto de anuncios relacionados con la capacidad de rescate de los gobiernos. Con el fin de evaluar si se ha producido una transferencia de riesgo de los bancos a los soberanos (debido al seguro implícito), el segundo capítulo analiza la reacción de los bonos soberanos a rebajas en los *ratings* de los bancos. Por último, el tercer capítulo analiza, desde una perspectiva teórica, la interacción entre la liquidez y los requerimientos de capital, y su efecto sobre final la toma de riesgos de los bancos.

Introduction

The last financial crisis revealed several weaknesses in the European and international regulatory architecture, while highlighting the relationship between banks and their national sovereigns.

Problems in the banking sector created significant complications for their home sovereigns. Rescue packages and extensions of financial safety-nets for banks, left many governments highly indebted. As a consequence, concerns arose about the ability of governments to raise sufficient funds to bail out banks. This might be particularly troublesome for larger banks located in financially distressed countries as the would become *Too Big to Save*. These are banks that are so large that governments are not able to manage a bailout. The case of Iceland, with banks almost ten times as large as GDP, is a clear example of this situation. The implications for regulatory policies, financial stability and the consequences for taxpayers due to bailouts in distressed economies make the subject an important problem.

Government intervention came at a cost since financial instability was transfered from banks to their corresponding national sovereigns, leading to the sovereign debt crisis. This link between banks and sovereigns (which implies an increase in market fragmentation) is strengthened by the existence of implicit guarantees. When markets expect massive bailouts on the financial sector, there is a subsequent transfer of risk to the national governments (anticipating an increase in sovereign debt). Such was the case of Ireland during the last financial crisis.

Finally, the financial crisis exposed a significant gap in the regulatory framework, i.e. the lack of a formal standard regulating liquidity. Despite the highly developed structure on capital requirements, it was liquidity issues that triggered runs on some banks. As a response to this weakness, regulators have created a new set of liquidity requirements (i.e. *Liquidity Coverage Ratio* or *Net Stable Funding Ratio*. Nevertheless, such standards might be overlooking the potential effects that liquidity has on solvency risk. In general, these regulatory tools have been analyzed in isolation, neglecting the possibility of interactions in the optimal levels for the standards.

Throughout this Thesis I will try to address the aforementioned issues, expanding the literature on regulation, implicit guarantees and the sovereign-bank nexus.

In the first chapter entitled *"Government Finances, Banks Bailouts and Moral Hazard: Evidence from European Stock Markets"* (coauthored with Margarita Samartín and Gerald Dwyer) I explore the existence of *Too Big to Save* banks.[1] Using a sample of European listed banks and a series of events affecting governments' fiscal position, I performed an event study to assess if there is a relationship between governments' financial difficulties and banks' stock returns. Such a relationship might be evidencing the existence of *Too Big to Save* cases. Using this strategy, I find a significant reaction of banks' stock returns to news concerning governments' finances. Their returns fall in response to a deterioration of governments' financial situation. Nevertheless, I find little difference in the reaction between large and small banks. The bulk of the evidence points towards all banks in the sample being fairly likely to be bailed out. It might be argued that during the sovereign debt crisis *"No Bank was Too Small to Save"*.

[1] At the time when this Thesis was written, this chapter was under second round revision in the *Journal of Empirical Finance*.

In the second chapter of my Dissertation, *"Risk transfer and implicit insurance: The effect of banks' downgrades on sovereign debt"*, I study the sovereign-bank nexus and the risk transfer from banks to governments. Analyzing the reaction of sovereign bond spreads when banks' *standalone ratings* are downgraded, I assess and quantify the magnitude of this transfer. Such downgrades are not related to governments' capacity to bail out financial intermediaries, hence they can be seen as discrete increases in banks' perceived level of risk. Results show that downgrades lead to increases in sovereign spreads. Consistent with the idea that risk transfer arises due to bailout expectations, the effect is larger when banks' default risk is higher (i.e. the final rating is within non-investment grades) or the bank is larger (*Too Big to Fail* implicit subsidy). Nevertheless, in distressed economies the effect on larger banks is lower than average,consistent with the idea that some of these banks might have become *Too Big to Save*. This interpretation of the result is confirmed by the usual cross section analysis. Then, results suggest the existence of a significant transfer of risk stemming from governments' guarantees.

In the last chapter *"Risk-taking and optimal joint liquidity and capital requirements"* (coauthored with Demian Macedo and Sergio Vicente) I study the interaction between liquidity and capital requirements. For this purpose I develop a theoretical framework in which liquidity has a dual on bank's risk-taking decision. On the one hand, cash reduces the likelihood of failing due to high levels of deposit withdrawals. On the other hand, it reduces the amount invested in loans (profitable asset). This last effect reduces banks' charter value, leading to an increase of bank's endogenous credit risk. In this setting, capital reduces solvency risk (*"skin in the game"*), but it is a costly tool (i.e. capital is more expensive than deposits). A regulator will set both liquidity and capital requirements to maximize social welfare. In this context the model provides a relationship for the optimal capital and liquidity requirements. If capital is relatively cheap, the regulator will have incentives to increase its use, and liquidity will be costlier (in terms of forgone loan investments). Hence, the regulator would need to reduce the level of capital to compensate for the higher liquidity (substitution effect). The opposite occurs when capital is cheaper, i.e. capital and liquidity would be complementaries.

Overall, the three papers in this Dissertation provide evidence on the existence of implicit guarantees during the last financial crisis, a risk transfer from banks to governments, and the interaction between regulatory capital and liquidity standards.

The Thesis has the following structure: the first chapter presents the paper "Government Finances, Banks Bailouts and Moral Hazard: Evidence from European Stock Markets"; the second chapter consists of the paper "Risk transfer and implicit insurance: The effect of banks' downgrades on sovereign debt"; chapter three is the paper entitled "Risk-taking and optimal joint liquidity and capital requirements"; and the last chapter presents the main bibliography used in my Dissertation.

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Chapter 1

Government Finances, Banks Bailouts and Moral Hazard: Evidence from European Stock Markets

1.1 Introduction

The Financial Crisis of 2007-2008 has highlighted the relationship between banks' finances and government finances. Difficulties at banks created substantial financial difficulties for governments. Concerns that governments might not have access to sufficient funds to bail out very large banks may have created other problems. The term "Too Big to Save" (TBTS) banks refers to banks that are so large that the government cannot manage a bailout of them. The extreme case of such banks is Iceland, which had very large losses and banks' deposits that were ten times Iceland's GDP (Flannery 2009).

Until recently, the relationship between government finances and bank bailouts has been largely ignored, most plausibly because it was not particularly important. Banks in the Eurozone have expanded, though, with insurance provided by the country in which banks' headquarters are located.

As a result, the relationship between banks' sizes and the sizes of the home country has been attenuated if not severed. The possibility of a mis-match between the insured deposits and other liabilities in banks headquartered in a country and the government's access to funds at that scale is a real possibility.

As a consequence, a substantial recent literature has highlighted the relationship between governments' spending, taxes and debt and their ability to bail out banks (Rime, 2005; Allen et al., 2011a; Bertay et al., 2013; Demirgüç-Kunt and Huizinga, 2013; Zaghini, 2014). The Financial Crisis of 2007-2008 and the ensuing recession weakened governments' finances, reducing funds that might be used to bail out banks. When a government's financial position is impaired, the probability of banks being bailed out falls. Partly because of banks's scale, as in Iceland, and partly because of governments' financial difficulities for other reasons, larger banks might become Too Big to Save (TBTS). If larger banks are less likely to be bailed out, then adverse developments in governments' finances are likely to have less effect on those banks' stock returns.

Analyzing the relationship between governments' finances and banks' market value is an important issue in the aftermath of the financial crisis, particularly for distressed economies. The implications for regulatory policies, financial stability and the consequences for taxpayers due to bailouts in distressed economies make the subject an important problem.

The purpose of the paper is to analyze the effect on banks' stock returns of announcements concerning governments' fiscal affairs which are likely to have an effect on governments' willingness and ability to bail out banks. We analyze stock returns for all listed banks headquartered in countries perceived as having financial difficulties – Greece, Ireland, Italy, Spain and Portugal

– during the Sovereign Debt Crisis in Europe after the Financial Crisis of 2007-2008.

In general, we find that banks' returns decrease when announcements indicate that the governments' financial position is impaired. This is consistent with Acharya et al. (2014) findings: there is a significant financial relation between banks and governments that arises mainly due to explicit and implicit government guarantees. Our results indicate that investors were indeed concerned about the governments' ability to bail banks out. In general, the effect of these announcements does not significantly differ between large and small banks. Most of the evidence suggests that the market perceives all banks as Too Big to Fail (TBTF) and markets still expect bailouts as suggested by Dieckmann and Plank (2012). Some evidence is consistent with the proposition that large banks are Too Big to Save (TBTS) Demirgüç-Kunt and Huizinga (2013).[1]

We think our analysis has several advantages compared to the prior literature. Our sample of European banks includes systemic banks as defined by Demirgüç-Kunt and Huizinga, 2013 and Bertay et al., 2013) while maintaining reasonable comparability across countries. We think that the time period and countries used have a reasonable likelihood of TBTS banks. Using an event study to examine the relationship reduces concerns regarding endogeneity. The underlying events are news about governments' finances reflecting serious difficulties with the governments' overall budget.[2] Finally, an event study provides a neat interpretation in terms of abnormal excess returns caused by the events.

The rest of the paper is organized as follows: Section 1.2 presents a

[1]This does not imply that banks in some other time or place cannot be too big to save. The banks in Iceland were too big for Iceland's taxpayers to pay off the depositors.

[2]It is not possible to be certain that endogeneity is not a problem (Roberts and Whited, 2012).

literature review. Section 1.3 shows the empirical approach, data sources and develops the hypotheses to be tested. Section 4 presents the results and different layers of analysis and section 5 concludes.

1.2 Literature review

Our paper contributes to the literature on the too big to fail and too big to save problems, as well as to the literature on sovereigns and the financial sector. In the next pages, we summarize both strands of literature.

1.2.1 Market discipline, too big too fail and Too big to save

"Market discipline" is a term used to summarize the relationship between the riskiness of banks' activities and the responses by holders of the banks' liabilities. Riskier banks have a higher probability of defaulting on the holders of their liabilities and a higher expected return compensates holders of liabilities for this risk. As emphasized in the literature, this relationship limits the riskiness of banks' activities. In addition, market discipline is exercised by depositors when they withdraw funds due to perceived risk (Calomiris and Kahn, 1991).[3]

Therefore, potential losses borne by holders of banks' liabilities are the basis of market discipline. However, when bailouts are expected, market

[3]There are different ways to proxy for market discipline. For instance Gorton and Santomero (1990) and Flannery and Sorescu (1996) use the implied volatilities of subordinated debt, while Morgan and Stiroh (2001) use bond spreads as measures for market discipline. Martinez-Peria and Schmukler (2001) follow a different approach: they use deposit interest rates and deposits withdrawal rate to study market discipline. All these measures are ex-post. Others including Nier and Baumann (2006) and Bushman and Williams (2012) use ex-ante market discipline measures such as the level of capital buffers, the sensitivity of leverage to risk or even accounting disclosures.

discipline decreases or even vanishes. In particular, when deposit insurance schemes are set up or there is any type of implicit insurance, depositors no longer require a risk premium in exchange for risk nor run on banks, as the risk is transferred to the insurer (Demirgüç-Kunt and Huizinga, 2004; Baier et al., 2012).

Because of this change in relative prices, banks will increase risk taking, and will have incentives to become big to fail (TBTF). O'Hara and Shaw (1990) test this hypothesis using an event study and find that shareholders from TBTF banks received a positive wealth effect when the Comptroller of the Currency announced that a set of large banks would not be allowed to fail. This effect is a clear example on how bailout expectations affect banks' shareholders. Similarly, Penas and Unal (2004) find evidence consistent with the TBTF hypothesis analyzing the reaction of bond prices to M&A announcements.

For large enough banks though, governments might find challenges and even face bankruptcy when providing guarantees to the financial system (Allen et al., 2011a). Countries' public finances may restrain the possible solutions to banks' distress. It may be infeasible to provide funds to keep banks operating, at least for banks that are too big to save (TBTS). Countries belonging to a monetary union may be in an even worse situation since they cannot monetize these guarantees. If a government can issue debt only in foreign currency or otherwise inflation protected, the same situation arises. In Iceland, virtually all government debt was denominated in foreign currency or inflation protected.

Analyzing banks' ratings, Rime (2005) failed to find evidence consistent with the perception that larger banks are TBTS. Analyzing equity prices and CDS spreads, Demirgüç-Kunt and Huizinga (2013) find evidence suggesting that systemically larger banks (as measured by their liabilities to GDP ratio) have become TBTS. This situation is particularly worse in countries with large fiscal deficits and high levels of sovereign debt. Similarly Bertay et al. (2013) find that systemically larger banks present lower returns on assets and equity with no risk reduction, while their funding costs are more sensitive to risk measures (z-score). These results are consistent with the existence of banks that are TBTS.

1.2.2 Sovereigns and the financial sector

Dieckmann and Plank (2012) analyze sovereign CDS and find a significant risk transmission from banks to the public sector. This result is consistent with expectations of bailouts of banks by governments.

Acharya and Rajan (2013) develop a model to explain how myopic governments increase sovereign debt holdings by their own banks, increasing financial instability. Acharya and Steffen (2015) find evidence consistent with a carry-trade behavior when analyzing the risk flow from sovereigns to banks.

From a theoretical perspective, Acharya et al. (2014) and Leonello (2015) analyze the relationship between sovereign risk and bank risk. This link between banks and governments generates a feedback effect that arises due to bailout expectations and guarantees to the financial system. This framework is empirically confirmed when analyzing the relationship between bank and sovereigns CDS spreads (Acharya et al., 2014). This is a clear illustration on how bailout expectations have an effect on governments' perceived finances.

Finally, using bank data collected from the ECB stress-test, Beltratti and Stulz (2015) conduct an event study using the CDS price on government debt and find that the stock prices for all the banks in a country to be negatively affected by a large increase in the price of the country's CDS, and that the stock price of banks with a larger exposure to its country's debt are more negatively affected by a shock to the country's finances. Additionally, they find the largest sovereign exposure are by banks from peripheral countries to their own country's debt.

In this paper, we examine the existence of a link between sovereign governments' finances and banks' risk due to government guarantees.

1.3 Hypotheses and Estimation Strategy

Our general assumption is that that a deterioration of a governments' fiscal position leads to a higher sensitivity of shareholders to banks' risk taking. This suggests that a negative announcement concerning a government's budget will generate a negative abnormal return for banks insured explicitly and implicitly by that government. Similarly, a positive development will generate a positive abnormal return.

Note that the problem that all of the country's faced was that their debts and those of their banks were denominated in a currency over which their government had no control: the euro. If the debt had been denominated in a currency over which the government had control, it could have paid its own debt and credibly guaranteed the nominal value of its banks' debt. Of course, that may have had some significant inflationary consequences.[4]

To focus on this issue, we study Greece, Ireland, Italy, Spain and Portugal during the Eurozone sovereign debt crisis after the Financial Crisis of 2007-2008. When we use dates of the sovereign-debt crisis, we define that period as extending from October 1, 2009 to the end of our data in December 2012

[4]We thank one of the reviewers for pointing this out. This fact is also mentioned in (Allen et al., 2011a).

(Lane, 2012).

1.3.1 Hypotheses

The general assumption of a relationship between government finances and banks' stock returns is reflected in the following hypothesis:

H_1**:** *Events affecting governments' fiscal positions are positively correlated with banks' abnormal stock returns.*
No such relationship could mean one of several things. It could be that banks (as a portfolio) never had implicit insurance, the event was too small to affect bailout expectations, or the event was fully anticipated.

We also are interested in the differential reaction between larger and smaller banks.

H_2**:** *Events affecting governments' fiscal position have a larger effect on larger banks' stock returns, if larger banks are regarded as too big to save.*
This hypothesis is consistent with the TBTS proposition put forth by Demirgüç-Kunt and Huizinga (2013), Bertay et al. (2013) and Allen et al. (2011a). When a governments' fiscal situation deteriorates, it is more likely that the government will not bail out larger financial institutions. Stockholders are less likely to be bailed out and are more exposed to banks' risk, which generates a negative abnormal stock return. If the opposite relationship holds with larger banks' returns less affected than smaller banks' returns, such results are more consistent with larger banks being regarded as too big to fail with stockholders in smaller banks not being bailed out.

1.3.2 Events

Events are selected considering two elements: their association with governments' ability to bail out banks; and the extent to which the events are unexpected. The latter is a major issue since expectations play a key role in our analysis. If an event is predicted perfectly, then abnormal returns are unaffected. It is not an easy task to determine the extent to which an announcement is actually unexpected. We try to tackle this issue using several strategies. First, we focus on a crisis time period. During calmer periods, policy announcements may be be more accurately anticipated than in a crisis one (Ait-Sahalia et al., 2012). Second, many of our events are watershed policy events as presented by media (similar to Ait-Sahalia et al., 2012).

We analyze a set of events that can be classified into five broad categories. In all, we have 57 events. Table 1.2 presents the number of the various types of events for each country.

- *Financial aid request*: governments formally request financial help from the ECB. We obtain the dates of such announcements from the ECB.[5] The effect of these particular announcements might go in either direction. On the one hand it is a clear signal that the financial health of the sovereign country is jeopardized, for which we would expect a negative reaction on the market. On the other hand, the announcement might be interpreted as a possible inflow of fresh funds to the governments.

- *Financial aid approved*: the IMF, the ECB and the European Com-

[5] Data were gathered from the ECB's "*Key dates of the financial crisis*" timeline (`http://www.ecb.europa.eu/ecb/html/crisis.en.html`). Additionally, we use Bloomberg's "*Greek Crisis Timeline*" to double check the announcements (`http://www.bloomberg.com/news/2012-09-05/greek-crisis-timeline-from-maastricht-treaty-to-ecb-bond-buying.html`). We add the date in which the 2^{nd} bailout to Greece was agreed by the Euro-area finance ministers.

mission agree on financial aid packages to troubled economies. These dates also are from the ECB. We expect that these announcements have a positive effect on banks' returns. Among this type of events, we include the second bailout agreement for Greece in which the "voluntary contribution of the private sector" implied in the end a 53.5% write-down for private Greek bond holders in the 'selective default'.

- *Sovereign downgrades*: announcements of downgrades of sovereign bonds by Moody's. The dates of these announcements are from Moody's web page for the '2007-2012' period. A downgrade on sovereign debt suggests a higher cost of debt for the government and a lower ability to issue new 'affordable' debt, which impairs its bailout capacity. It might seem that a decrease in the sovereign debt's rating implies a subsequent downgrade in the banks' rating. This is not the case because the upper bound for a firms' rating is the corresponding 'country ceiling' and not sovereign debt ratings.[6]

- *Forecasts revisions*: press releases in which debt forecasts (for previous or future periods) are revised upwards by any relevant institutions. These institutions are national governments, central banks, and European organizations such as Eurostat. Clearly, these announcements have a negative effect on governments' perceived fiscal position and ultimately on bailout capacity. These announcements and the dates are gathered from major press media (New York Times, Wall Street Journal, Financial Times, Bloomberg and Reuters). We use well known international mainstream financial media to avoid selection of irrele-

[6] For our 25 downgrades there are only 2 cases in which there was also a downgrade of the country ceiling (Italian and Spanish downgrades during 2012). Results are robust if these two cases are excluded.

vant information for the markets. To gather these announcements we mainly used the LexisNexis database.[7] We only consider those cases in which there is an explicit recognition of the change in the forecast or the estimation of deficit or debt. Even though we standardize the search process and try to make it as comprehensive as possible, there is some arbitrariness involved. Even so, it is replicable.

- *Suspension of eligibility*: the governing council of the ECB suspends the acceptability of marketable debt instruments issued or guaranteed by a government as collateral. The dates of these announcements are obtained from the ECB's web page. These events are expected to have a negative effect on governments' finances because their bonds and bonds guaranteed by them are likely to be viewed as riskier.

1.3.3 Methodology

We use event studies to analyze the reaction of banks' stock returns to a set of announcements regarding governments' finances. Event studies are a way to evaluate whether news about some specific event affects stock returns. The classical approach by Kothari and Warner (2007) uses residuals from an estimated market model around the date of the event and t-tests.[8]

An alternative procedure is to analyze abnormal returns using estimated regressions. Ongena et al. (2003) use this approach to evaluate the impact of announcements concerning troubled banks on the stock returns of related firms. Afonso et al. (2012) use it to analyze the effect of rating downgrades on sovereign bond yields and CDS spreads. This approach uses dummy

[7] The data appendix provides a description of the exact parameters used for this search.

[8] Kothari and Warner (2007) argue that when using short-term horizon events, the test statistic is not very sensitive to the model used to estimate normal returns.

variables on the days of the events and surrounding dates in a market model regression:[9]

$$R_{i,t} = \alpha_i + \beta_i R_{m,t}^{local} + \eta_i R_{m,t}^{global} + \sum_{k=-\tau}^{+\tau} \gamma_{i,k} \delta_{i,k,t} + \epsilon_{i,t} \tag{1.1}$$

where $R_{i,t}$ is the return of bank i in period t, $R_{m,t}^{local}$ is the market return for a particular country (e.g. IBEX) in period t. In order to account for a common factor that affects all banks across countries, we introduce the return on a Eurozone market index, $R_{m,t}^{global}$ (Euro Stoxx 50). Finally $\delta_{i,k,t}$ is a dummy variable that takes the value 1 if bank i has an event in period t for the event window k. This setting is used for each type of event.[10] Then, the cumulative abnormal return for a particular event window and event-type is given by the sum of the corresponding dummy variables. For instance, for the three day CAR[-1,+1] for firm i we would compute:

$$CAR_i\left(-1,+1\right) = \hat{\gamma}_{i,-1} + \hat{\gamma}_{i,0} + \hat{\gamma}_{i,+1} \tag{1.2}$$

We do not have enough observations between events to construct a market model for each event and the regression obviates making arbitrary choices of dates and overlap for events. We analyze the relationship between banks' stock returns and governments' finances in several different ways.

First, we analyze the effects of the selected events on banks' stock returns.

[9]Given the nature of our experiment and the timing of the events (and the reactions we measure), we would expect that reverse causality is not a severe issue in this study, In general, the events we have selected involve a certain time before any announcement can be made. Hence, any variation in banks' stock returns around the day of the announcement is not likely to influence or trigger the event itself. For example, the fact that Moody's announced a downgrade on sovereign debt for a particular country is not related to the volatility of banks' stock returns surrounding the day of the announcement. If any, this feature would strengthen our results. As there might be a partial anticipation to our events, the reaction we are able to measure represents only a proportion of the overall reaction associated with the event.

[10]We use clustered standard errors in our regression analysis.

This provides evidence on the general market reaction to these events and the expected direction of the effects on the returns as in equation (1.1). We then add interactions terms between the dummy variables for events and a systemic-size dummy variable to equation (1.1) and estimate:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t}^{local} + \eta_i R_{m,t}^{global} + \sum_{k=-\tau}^{+\tau} \gamma_{i,k}\delta_{i,k,t} + \sum_{k=-\tau}^{+\tau} \phi_{i,k}(\delta_{i,k,t} \times Size_{i,t}) + \epsilon_{i,t} \tag{1.3}$$

We use several alternative systemic-size dummy variables. These dummy variables take the value one if the systemic size of the bank is above a certain threshold and zero otherwise. Following Demirgüç-Kunt and Huizinga (2013), we use four different thresholds, 10%, 25%, 50% and 100%. A 10 per cent threshold would mean that those banks that have a ratio of Liabilities to GDP above 10 per cent would qualify as systematic. The same definition applies for the rest of the thresholds. This analysis allows to look for larger or smaller effects on systemically larger banks.

As a second approach, we aggregate banks' returns into portfolios at the country level. This reduces the effect of individual banks' idiosyncratic risk and emphasizes common factors affecting all banks in a country. We build two portfolios by country: one for large banks and one for smaller banks. We repeat this procedure using different size thresholds to determine the banks in each portfolio. We follow Demirgüç-Kunt and Huizinga (2013) in their definition of systemic size for the different thresholds used. These data then are used to estimate whether there is a differential effect on returns between the portfolios and evaluate its significance in the regression:

$$(R_{i,t}^{Large} - R_{i,t}^{Small}) = \alpha_i + \beta_i R_{m,t}^{local} + \eta_i R_{m,t}^{global} + \sum_{k=-\tau}^{+\tau} \gamma_{i,k}\delta_{i,k,t} + \epsilon_{i,t} \tag{1.4}$$

As a check on the sensitivity of the results to other variables, we repeat the original regression (1.1) with control variables added for banks' characteristics in addition to fixed effects for each bank to check whether these variables affect the results. Among these variables we include the ratio between bank's net sovereign debt holdings from their home country (home bias) and their total assets. This information was collected from the EBA stress tests.[11]

Because the sovereign-debt crisis itself may have affected responses to governments' financial difficulties, we also differentiate events occurring during the sovereign debt crisis. Given that we want to test if financially distressed governments are more or less likely to bail out banks, we test whether this effect was different during the sovereign crisis. We introduce time specific dummy variables and interactions in the basic regression analysis (1.1) and estimate:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t}^{local} + \eta_i R_{m,t}^{global} + \sum_{k=-\tau}^{+\tau} \gamma_{i,k}\delta_{i,k,t} + \phi Sov_{\cdot t} + \sum_{k=-\tau}^{+\tau} \xi_{i,k}(\delta_{i,k,t} \times Sov_t) + \epsilon_{i,t} \tag{1.5}$$

The variable Sov_t is a dummy variable which equals one during the sovereign debt crisis and zero otherwise. For our purposes, the sovereign-debt crisis starts in October 2009 and continues until the end of our data in December 2012 (Lane, 2012).

To further check our results, we examine whether the banks' abnormal returns are related to the banks' characteristics and variables related to

[11] One caveat is that our accounting information is annual but market returns reflect information daily. Additionally, the EBA stress tests did not cover all the banks/years we analyze. For those years and banks for which we do not have information on sovereign debt holdings, we set de value at zero. As robustness, we use the average or the last available information, and results are not qualitatively different.

bailouts. Using the regression analysis, we estimate an abnormal return for each individual event based on a unique dummy variable for each event.[12] These individual abnormal returns are the estimated γ coefficients from equation (1.1) for each individual event. In this case, the estimation is using country and day fixed effects. Then we perform a cross-section analysis in which these abnormal returns are regressed on a set of bank level characteristics including banks' sizes, systemic sizes as well as their home countries' government debt ratio. Additionally we include bank's sovereign exposure to their home country. This is in order to control for the alternative explanation of the bank-sovereign vicious circle, i.e. it is banks' sovereign debt holdings that explains most of the relationship (rather than the probability of bailout). Finally, we control for a set of bank level characteristics.[13] This regression is repeated for each event type:

$$AR_{i,t} = \alpha_i + Size_{i,t} + Sys.Size_{i,t} + Gov.Debt_{i,t} + NetSov.Debt_{i,t} + Controls_{i,t} + \epsilon_{i,t} \tag{1.6}$$

These controls are the Liquidity Ratio, the Equity Ratio, ROA and z-score. The Liquidity Ratio is the ratio of banks' cash holdings to total assets. The Equity Ratio is the ratio between banks' equity and total assets. The z-score is estimated using the equity's volatility for all the period.

Table 1.1 presents the number of banks for each country that meet different size thresholds – 10% , 25% or 50% as previous literature suggests – which are intended to represent possibly systemically important sizes.

[12] These dummy variables are constructed at the individual-event level, while the original analysis used dummy variables at the event-type level.

[13] One potential concern in this analysis, stems from the lack of dispersion in the controls for some types of events which occur seldom and then in the same year.

1.3.4 Data

We analyze stock returns for a set of publicly listed European banks after the financial crisis during the Fall 2008. There are two main reasons for the time period selected. During a crisis, policy announcements and other related events are less anticipated than during normal times (Ait-Sahalia et al., 2012). Additionally, many European countries were highly indebted with increasing borrowing costs, which limited their ability to bail out banks. We include banks headquartered in Greece, Ireland, Italy, Spain and Portugal. Figure 1.1 shows government debt and deficits relative to GDP for these countries.

Data for stock returns are obtained from DataStream. We include every firm which is classified as a bank by Thomson Reuters.[14] We complete this list using Bankscope because DataStream classifies some banks as financial sector firms. Adding Bankscope's banks ensures a more complete set of banks in these countries. Finally, we obtain data on bank's individual sovereign debt holdings from the EU-wide stress test. This information is available on EBA's web page. We keep only stocks for which we have a measure of 'adjusted prices', which correspond to the primary quote of the firm. We consider only those banks for which the stock was actively traded during the period of interest (around each event). We have 56 banks with data available from January 2007 to December 2012.[15] Table 1.1 shows the distribution of banks among countries. Bank-level accounting information is obtained from Bankscope. Data for the market indexes (both the 'specific country' and

[14] DataStream classifies companies as banks based upon the main activity of the company.

[15] By the end of 2012, the European Stability Mechanism (ESM) entered into force with the objective to provide for a permanent rescue funding programme for Member States. In this case governments' bailout capacity would be better guaranteed. This would reduce the bank-sovereign nexus and the interest of our analysis.

the Eurozone index) are obtained from DataStream. These are the usual benchmarks used at the country and Euro-area level.

1.4 Empirical results

1.4.1 The effect of events on banks' stock returns

We regress the returns for each individual bank on the corresponding market return in the country, the Eurozone market return and a set of dummy variables that take the value one if there was an event of the corresponding type that day and zero otherwise. Additionally, we include dummy variables that take the value of one on the day before and the day after the event to estimate the CAR from $t-k$ to $t+k$ where k varies from one to five. This procedure is repeated for each event type. All regressions are estimated using bank and year fixed effects (see equation 1.1).

The results for the regression analysis are presented in table 1.3 using a 3-day event window.[16] The cumulative effects are presented in Table 1.4 with the corresponding tests of joint significance for the abnormal returns using 3,5,7 and 11-days windows for each type of event.

We start analyzing the 3-day window (column *(1)* from Table 1.4). The coefficient for Financial Aid Approved is positive and statistically significant. This is consistent with the existence of a general explicit or implicit insurance and a resulting positive relationship between improving government finances and banks' stock returns. The dummy variable Financial Aid Request has a negative and statistically significant coefficient. This explicit recognition of

[16] We consider this is a sufficiently narrow window and it would not be contaminated. Additionally, it allows to capture some anticipated effect of the announcements, and account for any lagged reaction on the market (particularly important for those cases in which the announcement was made outside trading hours).

government's financial difficulties is associated with lower stock returns for banks, consistent with banks' reliance on government's guarantees. Similarly, the dummy variable for Sovereign Downgrades has a negative and highly significant coefficient. A lower credit rating implies a higher cost of issuing government debt and a higher cost of raising funds to bail out financial institutions. The dummy variable Suspension of Eligibility also has a negative and significant coefficient, which is consistent with the rationale for the other coefficients.

These results are consistent with the existence of a general explicit and implicit insurance to banks which is perceived to be impaired when governments finances deteriorate.

Table 1.4 columns *(2)* to *(4)* presents the results for additional event windows. Expanding the event window to 5-days (-1,+3), does not alter substantially our previous conclusions. All coefficients have the same signs. The effect of Financial Aid Approved and Financial Aid Request increases in magnitude and significance level. The Sovereign Downgrade has a larger coefficient which remains statistically significant. The dummy variable Suspension of Eligibility losses all of its explanatory power when expanding the event window. These results are consistent with the fact that stock returns take a few days to fully reflect announcements. The estimates for the 7-day window (-3,+3) lead to similar inferences. Extending the analysis to an 11-day event window (-5,+5) reduces the stastical significance level, which can be interpreted as indicating the window is longer than necessary to reflect effects on returns.[17]

These results are consistent with a statistically and economically significant reaction of bank' stock returns to announcements concerning govern-

[17]There is an exception: the coefficient for the dummy variable Forecast Revision becomes highly significant and negative.

ments' fiscal soundness. For relatively wider event windows, the reaction seems to become less important for most types of events with the exception of Forecast Revisions.

As mentioned above, part of the effect might be increased due to the sovereign debt crisis. We test this suggestion by estimating equation (1.5). Results for the 3-day window are presented in Table 1.5. [18] Because all of the events for Financial Aid Approved, Financial Aid Request and Suspension of Eligibility occur during the sovereign crisis, we omit interaction coefficients for these events. The most important change is for Sovereign Downgrades. The overall reaction to these events is significantly larger than before (still negative and highly significant at 1% level). Somewhat surprisingly, the additional effect of these downgrades during the sovereign debt crisis is positive and statistically significant. Nevertheless the magnitude is relatively small, and the total effect for this type of events remains negative and statistically significant. (This test is not reported).

Finally, we include a set of additional controls in our basic regression. These are bank level characteristics collected from their accounting statements, and sovereign exposure to their home country from the EU-wide stress tests. Table 1.6 presents the regression using a 3-day window, and Table 1.7 presents the corresponding CAR (and significance level) for 3, 5 and 7-days windows.

The results are consistent with the baseline analysis in terms of the magnitude and direction of the coefficients as well as their significance level. An interesting difference is the coefficient for Forecast Revision which becomes significant and negative for narrower event windows. As we increase the width of the event windows, these coefficient tend to become less significant

[18]Using different event windows does not qualitatively affect these results, and therefore we do not report these tables.

but this reduction is lower than in the baseline scenario.

All these results indicate the existence of a significant reaction of banks' stock returns to announcements regarding government's financial health. The evidence is consistent with the proposition that banks are perceived as having a partial guarantee by the government and developments affecting governments' finances affects banks' stock returns. We now test whether this reaction is related to banks' size, whether it only that some banks are too big to save and to what extent banks can be too big to save.

1.4.2 Banks' sizes, too big to fail and too big to save

Baseline approach

In this section we analyze whether there is a differential reaction to the same set of events depending on banks' size and try to assess whether larger banks may be too big to fail or too big to save. Demirgüç-Kunt and Huizinga (2013)'s results suggest that the relationship between banks' returns and size may not be linear. In order to test whether larger banks have a differential reaction to news, we use interactions between dummy variables for events and a systemic-size dummy as in equation (1.3). These interactions show the additional effect of size. Under the TBTF and TBTS hypotheses, these interactions are important. If large banks are too big to fail, the interaction effect will not be important. If banks are too big to save, an announcement concerning government finances will have a larger effect on larger banks.

Table 1.8 presents the results using the four different size thresholds. For simplicity we only tabulate the 3-day window (-1,+1). Consistent with our previous results, for the 10% threshold (column *(1)*) most of the event dummy variables remain highly significant (except for the Forecast Revision and the Financial Aid Approved events). Nevertheless only the Forecast Revision interaction is negative and statistically significant (at a 5% level). This interaction suggests that upward revisions in governments' debt ratios affect larger banks relatively more than smaller banks. This is consistent with the TBTS hypothesis. Analyzing the 25% threshold (column *(2)*) does not substantially affect the previous results: most of the dummy variables are significant (including Forecast Revision now), but only the interaction between Systemic Size and Forecast Revision is significant (with a marginally lower significance level). Again, these results provide some limited evidence consistent with the existence of TBTS banks. Column *(3)* presents the results for the 50% size threshold. The event dummy variables remain mostly unchanged, but there are some significant changes in the interaction terms. In this case the additional effect of Forecast Revision on large banks disappears, while the interaction coefficient for the Suspension of Eligibility becomes significant and positive. Both effects are inconsistent with the TBTS hypothesis. The effect of Forecast Revision on larger banks is not significantly different than the average, while the negative effect of Suspension of Eligibility events on larger banks is significantly smaller than the average. Finally column *(4)* presents the results for the 100% size threshold. In this case all the event dummy variables are statistically significant. With respect to the size-interactions, the coefficient for the Forecast Revision events becomes statistically significant but positive. This means that larger banks are significantly less negatively affected by these announcements than average. This evidence is consistent with the idea that these larger banks are still implicitly insured (not TBTS). The size interaction for the Suspension of Eligibility coefficient is not included since all banks affected by these announcements are smaller than 100%.

As a complementary test, Table 1.9 presents the results for the analysis in equation (1.3) with bank-level controls for accounting variables. As before, columns *(1)* to *(4)* present the information for different size thresholds. The main conclusions of this test are not different from the previous analysis. The effect of the announcements on larger banks is not more important than average. In fact, in some cases the effect on larger banks is significantly smaller than the average.

Taken altogether, this evidence casts reasonable doubt about the proposition that larger banks are too big to save in this episode. It seems that larger banks are not significantly more affected than smaller banks (or even less negatively affected), suggesting that they are still protected.[19]

Portfolio **approach**

As an alternative approach to assess the relationship between banks' stock return and governments' finances, we build two different portfolios at the country level based on banks' systemic size. We use four different thresholds to differentiate small from large banks. Following Demirgüç-Kunt and Huizinga 2013, we sequentially use the 10%, 25%, 50% and 100% thresholds. We then compute the mean return for each portfolio and calculate the difference in returns between large and small banks. We examine this difference in returns in a regression analysis with the market return and the event dummy variables. We use country and year fixed effects. If there are differential effects on large and small banks, the coefficients of these dummy variables should be significant with the sign depending on whether larger

[19]Edward Kane suggested an alternative interpretation of these results. It might be possible that the U.S. Federal Reserve is acting as a de facto global lender of last resort. If this is correct, then it does not matter whether European governments cannot bail out banks because the Federal Reserve would do so.

banks are too big to fail or too big to save.

Table 1.10 presents the analysis using a 3-day event window. Columns *(1)* to *(4)* show the results using the 10% up to the 100% thresholds to create the portfolios corresponding to large and small banks. None of the coefficients is statistically significant, with the exception of Suspension of Eligibility. Larger banks' average reaction is not different from smaller banks. For the case of Suspension of Eligibility, the smaller reaction of smaller banks with respect to larger banks is consistent with too big to fail.

Table 1.11 presents the same analysis extending the event window to 5 days (-1,+3). As in the previous case, columns *(1)* to *(4)* show the analysis through different size-thresholds. The results for the 10% size threshold confirm our previous conclusions: larger banks are not significantly more affected than smaller banks. Furthermore, the coefficients for Sovereign Downgrade and Suspension of Eligibility show that smaller banks reacted significantly more than larger banks. This evidence provides some support that larger banks are more likely to be bailed out, as suggested by TBTF. The same results and conclusions hold for the 25% size threshold analysis. For the 50% threshold, the coefficient of Financial Aid Approved event is positive and significant and consistent with the TBTS hypothesis. Nevertheless, the coefficient for the Financial Aid Approved (positive and significant) conflicts. Similarly, the coefficient for Suspension of Eligibility does not support the TBTS hypothesis. Finally, the 100% threshold leads to a similar conclusion. Both the coefficients for Forecast Revision and Suspension of Eligibility are positive and significant, i.e. smaller banks reacted more to these set of events.

Table 1.12 presents the same sort of analysis using a 7-day window (-3,+3). Using a 10% size threshold most of the coefficients are not significant, i.e. the difference in mean returns between large and small banks is not statistically different. Nevertheless, it is not the case for Suspension of Eligibility, that has a negative and significant coefficient. This means that larger banks are more affected than smaller banks (considering a wider event window), consistent with the idea that these banks might be considered TBTS. Similar results hold for the 25% threshold. However, as we increase the size threshold this effect disappears. The coefficient for Suspension of Eligibility events, when using the 50% threshold, becomes negative. Smaller banks reacted more than larger ones, which is against the TBTS hypothesis. Finally, analyzing the 100% size threshold only the coefficient for Financial Aid Approved events is consistent with the TBTS rationale. The coefficients for Forecast Revision and Suspension of Eligibility are positive and significant, which is incompatible with the TBTS explanation.

As in the baseline analysis, there is some evidence consistent with TBTF and bits of evidence consistent with TBTS. Overall, we interpret the evidence as more consistent with an hypothesis that No Bank is Too Small to Save.

Cross section analysis approach

We also carry out a cross-section analysis of the results assuming a linear relationship between abnormal returns and size, systemic size and the ratio of government debt to GDP. We estimate banks' abnormal returns for each individual event. We use the basic equation (1.1) with country and day fixed effects to estimate the corresponding 3-day reaction for each individual event, i.e. the γ coefficient for each individual event. Then we regress these abnormal returns on banks' size, systemic size, the ratio of government debt to GDP, the ratio of sovereign debt holdings and the set of bank level controls (equation 1.6).

Table 1.13 presents the cross-section analysis for the Financial Aid Approved events. For most of the specifications, the government-debt to GDP ratio has a negative and statistically significant coefficient. The positive effect of these announcements on banks is lower when government's debt is higher. This evidence can be interpreted as consistent with more distressed governments being less likely to bail out banks. This lower likelihood decreases the reaction of banks' stock returns to a favorable event. None of the systemic size dummy variables has a statistically significant coefficient. There is one specification in which size has a positive and significant coefficient, which means that larger banks reacted more importantly to this sort of announcements. But this concerns one of out five results and it is hardly overwhelming.

Table 1.14 shows the analysis for Financial Aid Requests. The effect of government-debt to GDP is positive and significant across all specifications. This means that the negative effect on banks' returns of this type of announcements (recall the results from Table 1.4) is mitigated when governments are highly indebted. Even though these announcements implicitly recognize government's poor financial situation, this can be interpreted as indicating a possible later inflow of funds. None of the regressions suggests differential effects across large and small banks.

The results for Forecast Revisions are presented in Table 1.15. There is only one statistically significant coefficient at the ten percent significance level for size, out of five estimated coefficients. There is one coefficient of systemic size statistically significant at the five percent level and another at the ten percent level. None of the coefficients of the ratio of government debt to GDP is statistically significant. Overall, this evidence suggests that banks' abnormal returns associated with Forecast Revisions are hardly affected by government debt and systemic size considerations.

Finally, Table 1.16 shows the results for Sovereign Downgrades. The coefficient of the ratio of government debt to GDP is consistently negative and statistically significant at the ten percent level across specifications. Banks located in more indebted economies are more negatively affected by these announcements. Additionally in two specifications the coefficient for Size is negative and significant at the ten percent and in one specification it is significant at the five percent. This suggests that larger banks reacted more to this sort of announcements. Systemic Size have no effect on the magnitude of the reaction in none of the equations, with statistically insignificant and numerically small coefficients.

The analysis for the Suspension of Eligibility events is not presented because most of the variables of interest are omitted due to perfect collinearity given the small sample size. The variables omitted and those left in are arbitrary and the results cannot be informative.[20]

1.5 Conclusions

In this paper, we use an event study, in order to see whether there is a relationship between governments' finances and the perceived likelihood that banks will be bailed out. We analyze the reactions of banks' stock returns to a series of announcements concerning governments' finances. The advantage of this type of analysis lies on its simplicity and the ease of interpreting the results while reducing endogeneity issues. These events are directly related to government's ability to bail out the banking system.

We find that the overall reaction of stock prices to these announcements is significant. Banks' return reacts negatively to adverse announcements con-

[20]No variable is statistically significant.

cerning government finances. This suggests that the perceived probability of stockholders being bailed out goes down when government finances deteriorate.

We find some evidence that larger banks are more affected than smaller banks, although it is not overwhelming. This conclusion remains valid using different approaches, i.e. the basic regression framework, regressions using mean portfolios analysis or using the usual cross section analysis.

For the Eurozone sovereign-debt crisis, the evidence indicates that No Bank is Too Small to be Save. We find a clear statistical association between banks' stock returns and announcements concerning governments' finances. We find bits of evidence supporting the propositions that larger banks are Too Big to Fail or Too Big to Save. The clearest evidence, though, is the regressions of returns of large banks minus the returns of small banks, which shows little evidence of any differential effect on large banks compared to small banks.

Tables

Table 1.1: Banks by Country

Market	Banks	10% Systemic Size	25% Systemic Size	50% Systemic Size
Greece	13	7	4	2
Ireland	4	4	4	3
Italy	21	3	2	1
Portugal	5	3	3	1
Spain	13	5	3	2
Total	**56**	**22**	**16**	**9**

Table 1.2: Event types by country

Type / Market	Greece	Ireland	Italy	Portugal	Spain	Total
Financial aid - Agreement	4	1	0	1	1	7
Financial aid - Request	1	1	0	1	1	4
Forecast revision	7	1	3	4	4	19
Moody's Downgrade	7	5	3	5	5	25
Suspension of eligibility	2	0	0	0	0	2
Total	**21**	**8**	**6**	**11**	**11**	**57**

Table 1.3: Regression Analysis - Bank level abnormal returns

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Local Market Index	1.2363***	1.2353***	1.2351***	1.2353***	1.2363***
Euro Market Index	-0.2837***	-0.2829***	-0.2828***	-0.2828***	-0.2840***
Financial Aid Approved					
t = -1	0.0062	-	-	-	-
t = 0	0.0120**	-	-	-	-
t = +1	0.0080*	-	-	-	-
Financial Aid Request					
t = -1	-	0.0007	-	-	-
t = 0	-	-0.0115	-	-	-
t = +1	-	-0.0173*	-	-	-
Forecast Revision					
t = -1	-	-	-0.002	-	-
t = 0	-	-	-0.0024	-	-
t = +1	-	-	-0.0038*	-	-
Sovereign Downgrade					
t = -1	-	-	-	0.0011	-
t = 0	-	-	-	-0.0042**	-
t = +1	-	-	-	-0.0069***	-
Suspension of Eligibility					
t = -1	-	-	-	-	-0.0087***
t = 0	-	-	-	-	-0.0277***
t = +1	-	-	-	-	0.0044
Constant	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
N	80021	80021	80021	80021	80021
$Adj.R^2$	0.2821	0.2821	0.282	0.2821	0.2821

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

The dependent variable is a Bank's Stock Return. Local Market Index is the return for the corresponding country benchmark index (vary across countries). Euro Market Index stands for the return of a common benchmark index (same for all countries). Column **(1)** presents the information for Financial Aid Approved events while column **(2)** presents the results for the Financial Aid Request events. Column **(3)** shows the results for the Forecast Revision dummy, and column **(4)** for Sovereign Downgrades events. Finally in column **(5)** we use the Suspension of Eligibility events. The coefficients for $t = -1$ corresponds to the abnormal reaction on bank's returns (for the corresponding type of event) the day before the event takes place. The coefficients for $t = 0$ and $t = +1$ correspond to the reaction on the day of the event, and the day following the even respectively. All regressions are using bank and year fixed effects.

Table 1.4: Bank's Abnormal Returns - 3, 5 , 7 & 11 days CAR

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	0.0262**	0.0328***	0.0554***	0.032**
Fin. Aid Request	-0.0281**	-0.0495***	-0.0347**	0.0092
Forecast Revision	-0.0083	-0.0008	-0.0041	-0.0324***
Sovereign Downgrade	-0.0099***	-0.0133***	-0.0112**	-0.0167*
Susp. of Elig.	-0.0319***	-0.011	0.0187	-0.0114

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Column **(1)** presents the information for the 3-day windows (-1,+1), column **(2)** for the 5-day windows (-1;+3), column **(3)** do so for the 7-day windows (-3,+3) and column **(4)** for the 11-day windows (-5,+5). Results correspond to the analysis of different event windows estimated using equations 1.1 and 1.2. All regressions are using bank and year fixed effects.

Table 1.5: Bank's Abnormal Returns - Sovereign Crisis Period

Type	**CAR[t-1; t+1]**	**P-Value**
Fin. Aid Approved	0.0262	0.0281
Fin. Aid Request	-0.0281	0.0204
Forecast Revision	-0.0006	0.8529
Sovereign Downgrade	-0.0813	0.0002
Susp. of Elig.	-0.0319	0.0000
Fin.Aid.Appr. × Sov. Crisis	(omitted)	(omitted)
Fin.Aid.Req. × Sov. Crisis	(omitted)	(omitted)
For.Rev. × Sov. Crisis	0.0024	0.3157
Sov.Downg. × Sov. Crisis	0.003	0.0011
Susp.Elig. × Sov. Crisis	(omitted)	(omitted)

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Interactions corresponding to rescue programs and suspension of eligibility are omitted due to collinearity. This arises since all these events occur during the sovereign debt crisis. All regressions are using bank and year fixed effects following equation (1.5).

Table 1.6: Regression Analysis - Bank level abnormal returns and bank characteristics

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Market Return	1.2196***	1.2186***	1.2186***	1.2189***	1.2195***
Euro-Market Return	-0.2676***	-0.2668***	-0.2667***	-0.2670***	-0.2680***
Systemic Size	-0.0004	-0.0002	-0.0002	-0.0002	-0.0001
Sovereign Exposure Ratio	-0.0059	-0.0059	-0.0056	-0.0058	-0.0061
Liquidity Ratio	- 0.0000	0.0001	0.0001	-0.0001	0.0001
Equity Ratio	-0.0146*	-0.0143*	-0.0143*	-0.0144*	-0.0153**
ROA	0.0181***	0.0174***	0.0165***	0.0172***	0.0179***
Size	-0.0022	-0.0023	-0.0022	-0.0022	-0.0025
Z-score	0.0001	0.0001	0.0001	0.0001	0.0001
Financial Aid Approved					
t = -1	0.0053	-	-	-	-
t = 0	0.0121*	-	-	-	-
t = +1	0.0088*	-	-	-	-
Financial Aid Request					
t = -1	-	0.0014	-	-	-
t = 0	-	-0.0121	-	-	-
t = +1	-	-0.0185*	-	-	-
Forecast Revision					
t = -1	-	-	-0.0075***	-	-
t = 0	-	-	-0.0019	-	-
t = +1	-	-	-0.0035*	-	-
Sovereign Downgrade					
t = -1	-	-	-	0.0006	-
t = 0	-	-	-	-0.0054***	-
t = +1	-	-	-	-0.0069***	-
Suspension of Eligibility					
t = -1	-	-	-	-	-0.0097***
t = 0	-	-	-	-	-0.0289***
t = +1	-	-	-	-	0.0018
Constant	0.0166	0.0169	0.0160	0.0161	0.0185
N	76329	76329	76329	76329	76329
$Adj.R^2$	0.306	0.306	0.306	0.306	0.306

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

The dependent variable is each bank's Stock Return. Local Market Index is the return for the corresponding country specific benchmark index. Euro Market Index stands for the return of a common benchmark index. Systemic Size is defined as banks' total liabilities to home country's GDP ratio. Sovereign Exposure Ratio is the ratio between bank's net sovereign debt holding of their home country to total assets. Liquidity Ratio is the ratio between banks' cash holdings to banks' total assets. Equity Ratio is the ratio of banks' equity to total asset. Size is the natural logarithm of banks' total assets. z-score is estimated using the equity's volatility for all the period under analysis. Column **(1)** presents the information for Financial Aid Approved events, column **(2)** presents the results for the Financial Aid Request events. Column **(3)** shows the results for the Forecast Revision dummy, and column **(4)** for Sovereign Downgrades events. Column **(5)** uses the Suspension of Eligibility events. The coefficients for $t = -1$ corresponds to the abnormal reaction on bank's returns the day before the event takes place. The coefficients for $t = 0$ and $t = +1$ correspond to the reaction on the day of the event, and the day following the even respectively. All regressions are using bank and year fixed effects.

Table 1.7: Bank's Abnormal Returns - 3, 5 & 7 days CAR - w/bank level characteristics

Type	**(1)**	**(2)**	**(3)**
Fin. Aid Approved	0.0261**	0.0276**	0.0515***
Fin. Aid Request	-0.0292**	-0.0512**	-0.0365**
Forecast Revision	-0.0128***	-0.0073*	-0.0095
Sovereign Downgrade	-0.0117***	-0.0153***	-0.0140**
Susp. of Elig.	-0.0369***	-0.0245**	0.0012

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Column **(1)** presents the information for the 3-day windows (-1,+1), column **(2)** for the 5-day windows (-1,+3), and column **(3)** do so for the 7-day windows (-3,+3). Results correspond to the analysis of different event windows estimated using the model controlling for bank level characteristics, including sovereign exposure. All regressions are using bank and year fixed effects.

Table 1.8: Banks' Abnormal Returns - Size interactions

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	0.0207	0.0185	0.0151	0.0211*
Fin. Aid Request	-0.024**	-0.0211*	-0.022**	-0.0224**
Forecast Revision	-0.0046	-0.0086**	-0.0127***	-0.014***
Sovereign Downgrade	-0.0097**	-0.0086***	-0.0095***	-0.0108***
Susp. of Elig.	-0.0397***	-0.0397***	-0.0409***	-0.0348***
Fin. Aid Ap. × size-X%	0.0078	0.0156	0.0541	0.1271
Fin. Aid Req. × size-X%	-0.0087	-0.0194	-0.0374	-0.106
Forecast Rev. × size-X%	-0.0184**	-0.0133*	-0.003	0.0314**
Sov. Down. × size-X%	-0.0046	-0.0092	-0.0141	-0.0256
Susp. of Elig. × size-X%	0.007	0.007	0.0216**	(omitted)

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Coefficients estimated using a 3-days event window (-1,+1). Column **(1)** presents the interactions using a 10% size-threshold dummy. Column **(2)** uses a 25% while column **(3)** a 50% threshold dummy. Finally column **(4)** presents the interactions using a 100% size-threshold dummy. Results correspond to the analysis using the basic model including interactions between size-thresholds and event dummy variables (equation 1.3). All regressions are using bank and year fixed effects.

Table 1.9: Banks' Abnormal Returns - Size interactions and bank level characteristics

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	0.0213	0.0192	0.0156	0.0217*
Fin. Aid Request	-0.0234*	-0.0204*	-0.0215**	-0.0218**
Forecast Revision	-0.0041	-0.0080**	-0.0123***	-0.0136***
Sovereign Downgrade	-0.0100**	-0.0086***	-0.0093***	-0.0105***
Susp. of Elig.	-0.0404***	-0.0407***	-0.0431***	-0.0368***
Fin. Aid Ap. × size-X%	0.0075	0.0151	0.0551	0.1244
Fin. Aid Req. × size-X%	-0.0088	-0.0196	-0.0369	-0.1092
Forecast Rev. × size-X%	-0.0190**	-0.0145*	-0.0025	0.0285**
Sov. Down. × size-X%	-0.0035	-0.0086	-0.0137	-0.0287
Susp. of Elig. × size-X%	0.0053	0.0056	0.023**	(omitted)

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Coefficients estimated using a 3-days event window (-1,+1). Column **(1)** presents the interactions using a 10% size-threshold dummy. Column **(2)** uses a 25% while column **(3)** a 50% threshold dummy. Finally column **(4)** presents the interactions using a 100% size-threshold dummy. Results correspond to the analysis using the basic model, including interactions between size-thresholds and event dummy variables (equation 1.3) controlling for bank level characteristics as well. All regressions are using bank and year fixed effects.

Table 1.10: Large vs. Small banks' portfolios - 3 days CAR

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	-0.0105	-0.0123	0.0218	-0.01
Fin. Aid Request	0.0288	0.0278	0.0017	-0.0435
Forecast Revision	-0.0064	0.0018	0.0115	0.0607
Sovereign Downgrade	0.0067	0.0047	-0.0026	0.0083
Susp. of Elig.	0.02***	0.0215***	0.033***	0.0171***

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

We split banks in to groups for each country/year, i.e. large vs small banks (using different thresholds). The mean return for each group is computed. The difference between these groups is the main dependent variable in this regression, using our previous set of dummy variables as in equation (1.4). Coefficients are estimated using a 3-days event window (-1,+1). Column **(1)** presents the results using a 10% size-threshold to differentiate groups. Column **(2)** uses a 25% while column **(3)** a 50% and column **(4)** uses a 100% size-threshold. All regressions are using country and year fixed effects.

Table 1.11: Large vs. Small banks' portfolios - 5 days CAR

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	0.0046	-0.0027	0.0255*	0.0095
Fin. Aid Request	0.0422	0.0352	0.039*	-0.0429
Forecast Revision	0.0022	0.0091	0.0006	0.0728*
Sovereign Downgrade	0.022**	0.0206**	-0.0011	0.0159
Susp. of Elig.	0.0189***	0.0197***	0.0404***	0.0542***

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$
We split banks in to groups for each country/year, i.e. large vs small banks (using different thresholds). The mean return for each group is computed. The difference between these groups is the main dependent variable in this regression, using our previous set of dummy variables as in equation (1.4). Coefficients are estimated using a 5-days event window (-1,+3). Column **(1)** presents the results using a 10% size-threshold to differentiate groups. Column **(2)** uses a 25% while column **(3)** a 50% and column **(4)** uses a 100% size-threshold. All regressions are using country and year fixed effects.

Table 1.12: Large vs. Small banks' portfolios - 7 days CAR

Type	**(1)**	**(2)**	**(3)**	**(4)**
Fin. Aid Approved	-0.008	-0.0013	0.0062	0.0165***
Fin. Aid Request	0.0391	0.0184	0.0019	-0.0634
Forecast Revision	0.0005	0.0058	-0.0017	0.0686*
Sovereign Downgrade	0.0224	0.0218*	-0.0161	-0.0018
Susp. of Elig.	-0.0144**	-0.0136**	0.0314***	0.0718***

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$
We split banks in to groups for each country/year, i.e. large vs small banks (using different thresholds). The mean return for each group is computed. The difference between these groups is the main dependent variable in this regression, using our previous set of dummy variables as in equation (1.4). Coefficients are estimated using a 7-days event window (-3,+3). Column **(1)** presents the results using a 10% size-threshold to differentiate groups. Column **(2)** uses a 25% while column **(3)** a 50% and column **(4)** uses a 100% size-threshold. All regressions are using country and year fixed effects.

Table 1.13: Cross section analysis - Financial Aid Approved events

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Size	0.0022	0.0775*	0.0190	0.0099	0.0196
Systemic Size	0.0418	-	-	-	-
Sys.Size 10%	-	-0.0768	-	-	-
Sys.Size 25%	-	-	-0.0016	-	-
Sys.Size 50%	-	-	-	0.0225	-
Sys.Size 100%	-	-	-	-	-0.0364
Govt.debt ratio	-0.2052**	-0.1197	-0.1813*	-0.1964**	-0.1856**
Sov. Exposure	0.6677*	0.7673*	0.6404	0.6793*	0.6432
N	57	57	57	57	57
$Adj.R^2$	0.5386	0.5652	0.5361	0.5407	0.5398

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

The dependent variable is each bank's Abnormal Return for a 3-day period estimated using the simple model from equation (1.1) computed with bank and day fixed effects. Size is the natural logarithm of banks' total assets. Systemic Size is banks' total liabilities to GDP ratio. Sys.Size X% is a dummy that equals 1 if bank's systemic size is above the X% threshold. Govt. debt ratio is total public debt to GDP. Sov. Exposure is the ratio between bank's sovereign debt holdings from their home country and total assets. We include other bank level controls: Liquidity Ratio, Equity Ratio, ROA and z-score. Cross section regressions is estimated using country and year fixed effects.

Table 1.14: Cross section analysis - Financial Aid Request events

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Size	0.0151	0.0117	0.0065	0.0132	0.0245
Systemic Size	0.0164	-	-	-	-
Sys.Size 10%	-	0.0140	-	-	-
Sys.Size 25%	-	-	0.0212	-	-
Sys.Size 50%	-	-	-	0.0203	-
Sys.Size 100%	-	-	-	-	-0.0169
Debt to GDP	0.3962***	0.3844***	0.3875***	0.4005***	0.3776***
Sov. Exposure	1.5116**	1.6040**	1.8575**	1.3600**	1.6385**
N	29	29	29	29	29
$Adj.R^2$	0.7290	0.7310	0.7393	0.7397	0.7321

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

The dependent variable is each bank's abnormal return for a 3-day period estimated using the simple model from equation (1.1) computed with bank and day fixed effects. Size is the natural logarithm of banks' total assets. Systemic Size is banks' total liabilities to GDP ratio. Sys.Size X% is a dummy that equals 1 if bank's systemic size is above the X% threshold. Govt. debt ratio is total public debt to GDP. Sov. Exposure is the ratio between bank's sovereign debt holdings from their home country and total assets. We include other bank level controls: Liquidity Ratio, Equity Ratio, ROA and z-score. Cross section regressions is estimated using country and year fixed effects.

Table 1.15: Cross section analysis - Forecast Revision events

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Size	-0.0181*	-0.0041	-0.0106	-0.0138	-0.0113
Systemic Size	0.0315	-	-	-	-
Sys.Size 10%		-0.0108	-	-	-
Sys.Size 25%			0.0026	-	-
Sys.Size 50%				0.0147	-
Sys.Size 100%	-	-	-	-	0.0301**
Debt to GDP	0.0703	0.0792	0.0744	0.0734	0.0730
Sov. Exposure	-0.1372	-0.1286	-0.1538	-0.1360	-0.1469
N	184	184	184	184	184
$Adj.R^2$	0.1080	0.1035	0.1005	0.1075	0.1083

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

The dependent variable is each bank's abnormal return for a 3-day period estimated using the simple model from equation (1.1) computed with bank and day fixed effects. Size is the natural logarithm of banks' total assets. Systemic Size is banks' total liabilities to GDP ratio. Sys.Size X% is a dummy that equals 1 if bank's systemic size is above the X% threshold. Govt. debt ratio is total public debt to GDP. Sov. Exposure is the ratio between bank's sovereign debt holdings from their home country and total assets. We include other bank level controls: Liquidity Ratio, Equity Ratio, ROA and z-score. Cross section regressions is estimated using country and year fixed effects.

Table 1.16: Cross section analysis - Sovereign Downgrade events

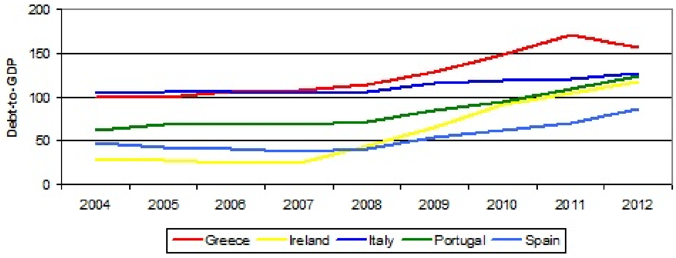
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Size	-0.0138	-0.0136	-0.0168**	-0.0124*	-0.0112*
Systemic Size	0.0074	-	-	-	-
Sys.Size 10%	-	0.0040	-	-	-
Sys.Size 25%	-	-	0.0104	-	-
Sys.Size 50%	-	-	-	0.0027	-
Sys.Size 100%	-	-	-	-	-0.0028
Debt to GDP	-0.1392*	-0.1414*	-0.1427*	-0.1396*	-0.1411*
Sov. Exposure	0.2402*	0.2283	0.2444*	0.2385*	0.2338
N	210	210	210	210	210
$Adj.R^2$	0.2195	0.2195	0.2224	0.2193	0.2191

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

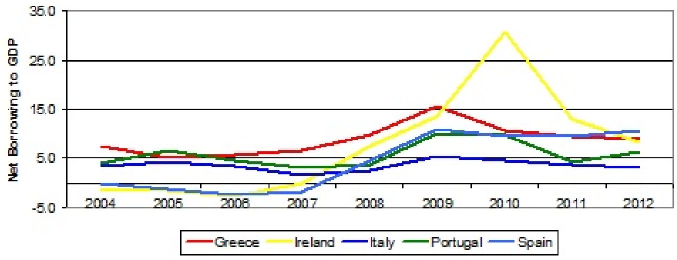
The dependent variable is each bank's abnormal return for a 3-day period estimated using the simple model from equation (1.1) computed with bank and day fixed effects. Size is the natural logarithm of banks' total assets. Systemic Size is banks' total liabilities to GDP ratio. Sys.Size X% is a dummy that equals 1 if bank's systemic size is above the X% threshold. Govt. debt ratio is total public debt to GDP. Sov. Exposure is the ratio between bank's sovereign debt holdings from their home country and total assets. We include other bank level controls: Liquidity Ratio, Equity Ratio, ROA and z-score. Cross section regressions is estimated using country and year fixed effects.

Figures

Figure 1.1: Gross debt to GDP ratio & Deficit to GDP ratio



(a) Gross debt to GDP ratio



(b) Deficit to GDP ratio

Source: Author's Elaboration based on Eurostat data

Figure 1.2: Financial aid agreement: Mean daily return around event

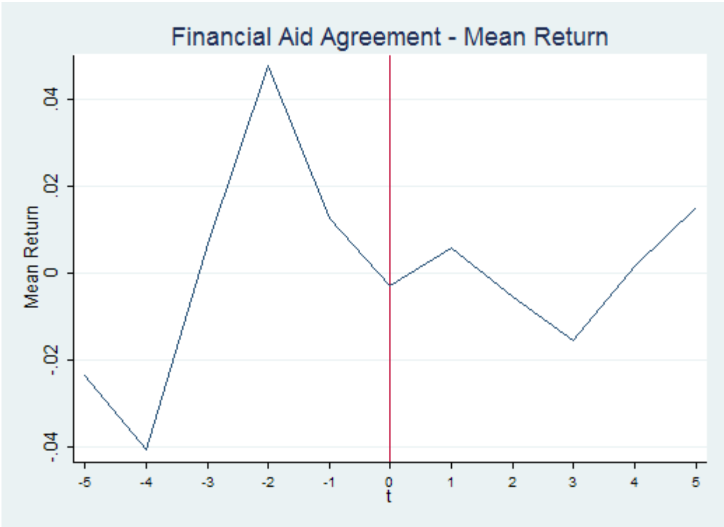


Figure 1.3: Financial aid request: Mean daily return around event

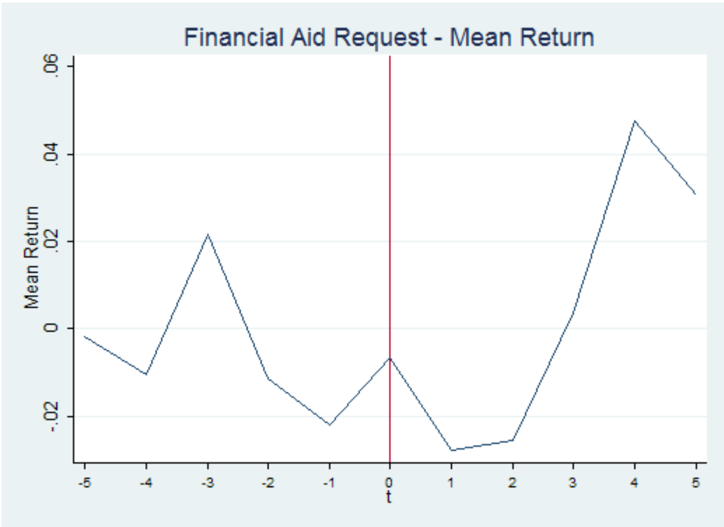


Figure 1.4: Forecast revision: Mean daily return around event

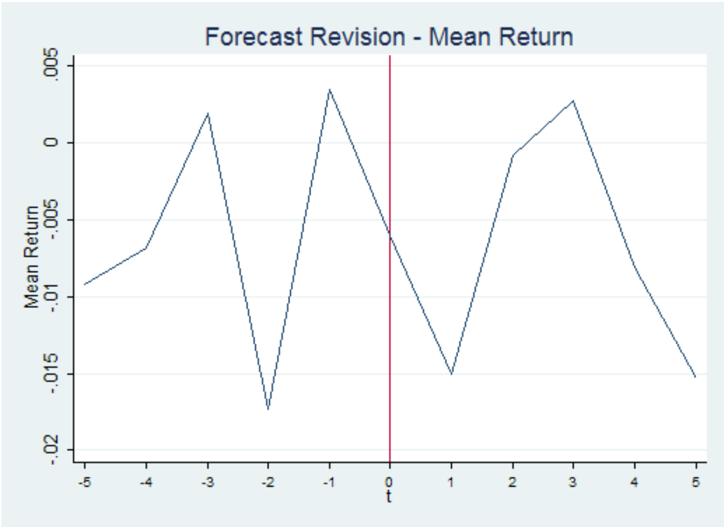


Figure 1.5: Moody's downgrade: Mean daily return around event

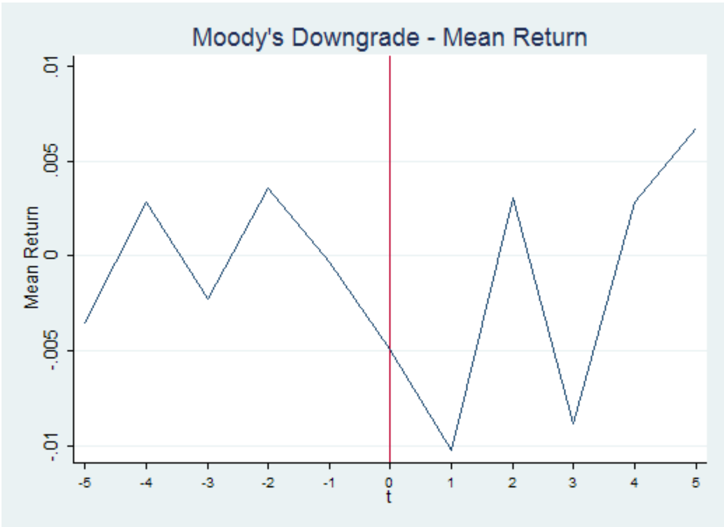
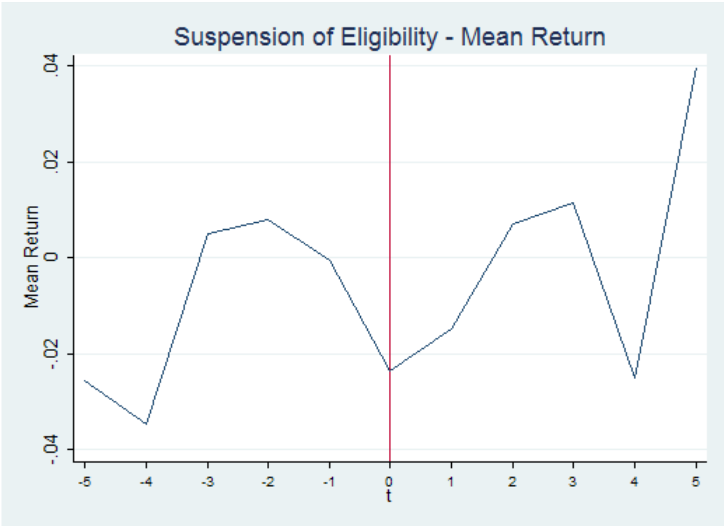


Figure 1.6: Suspension of eligibility: Mean daily return around event



Data Appendix

The parameters used in LexisNexis to look for 'Forecast Revisions' are:

- Dates: Jan.01, 2007 Dec.31, 2012.
- Countries: Greece, Ireland, Italy, Portugal, Spain.
- Subjects: Public Finance (alternatively we used: Gov. Budget + Gov. Grants and Subs. + Public Debt + Taxes and Taxation).
- Sources: Bloomberg Transcripts, Financial Times Online Archive, Financial Times (London) Archive, The New York Times, Wall Street Journal Abstracts and Wall Street Journal Report.
- Keywords:

  Forecast + debt,

  Forecast AND deficit,

  Forecast AND deficit AND (revise OR revision) AND (Greece OR Ireland OR Italy OR Portugal OR Spain).

It is worth mentioning that in general the events do not overlap considering a [-5,+5] window. There are a few exceptions for this.

On April 22nd, 2010, we find 2 different events for Greece. Moody's downgrade by 1 notch Greeks sovereigns and Eurostat announces an upward forecast revision on the level of debt. Both events are likely to move bank's returns on the same direction so it does not generate a problem.

Additionally the following day (April 23rd, 2010) Greece formally request financial aid from the EU. The expected reaction of bank's returns is not clear ex ante. The effect of the previous events might not go on the same direction.

If this is the case we might interpret that there is not a significant reaction, when this could not be the case. A similar situation occurs for Portugal on April 2011. On the 5th, Moody's downgraded Portuguese sovereign by one notch. The following day, Portugal requests the activation of aid mechanism. For both cases, we can interpret the financial aid request (from Greece and Portugal) as a reaction from the previous downgrade.

If we extend the window we find one case in which Moody's downgrades the Portuguese sovereign (by 4 notches into speculative grade) on July 5th, 2011. Two days afterwards, the ECB suspends any restrictions on the use of Portuguese bonds as collateral. We can interpret the ECB announcement as a reaction to the first event.

A similar situation occurs for Greece on July 21st, 2011. A second bailout is approved (which included some comments on "voluntary contribution of the private sector", or selective default). On July 25th Moody's downgraded 3 notches Greek debt rating (considering only trading days, these events would be separated by two days). Nevertheless we expect both events to go in the same direction.

Further increasing the window, we find some overlapping considering wider event windows. If we restrict its size, we avoid all of these problems. Additionally when using the regression analysis, overlapping would not generate any problem, even in wider event windows.

Chapter 2

Risk transfer and implicit insurance: The effect of banks' downgrades on sovereign debt

2.1 Introduction

During the last crisis many financial institutions were under severe distress. Explicit safety nets (e.g. deposit insurance schemes) and implicit guarantees ('Too Big to Fail'-*TBTF* subsidies) became more important for banks and other thrift institutions. Governments around the globe decided to bail out banks providing liquidity support, recapitalization programs, or offering larger guarantees on their liabilities (extending the safety nets coverage). But these government guarantees come at a cost since bank's financial instability was passed on to governments leading to a sovereign debt crisis (Dieckmann and Plank, 2012; Acharya et al., 2014; Leonello, 2015). This situation further worsened banks financial health due to a 'diabolic loop' (Acharya and Rajan, 2013; Gennaioli et al., 2014; Acharya and Steffen, 2015).

The link between the financial sector and sovereign default risk is a relatively new problem for advanced economies. A good example of this situation is the case of Ireland (Figure 2.1). After the Irish government announced a full insurance on all deposits for all major banks (September, 2008), there was a steep increase in the Irish sovereign CDS spread. On the other hand Iceland seems to be an interesting counter-factual: when it was clear that the Icelandic government was not going to bailout the financial system, spreads fell significantly (Acharya et al., 2014).

The sovereign crisis led to a related problem. Impaired governments are less likely to be able to extend guarantees to financial institutions. Then larger banks might become 'Too Big to Save' (*TBTS*) (Allen et al., 2011a; Bertay et al., 2013; Demirgüç-Kunt and Huizinga, 2013; Zaghini, 2014). The Icelandic case, where foreign depositors from larger banks were not rescued, illustrates this situation. This should reduce the link between the financial sector and governments, but at the cost of increasing the *'systemicity'* of these banks.[1]

In order to complement the existing literature I propose an event study similar to that of Ongena et al. (2003), and Afonso et al. (2012). For a number of Western Europe countries during the last financial crisis I examine the effects of downgrades on banks' financial strength ratings (Moody's Investors Service, 2013), a standalone rating, on sovereign bond spreads. These downgrades are considered as discrete increases in banks' default risk (Billett et al., 1998). Focusing on a crisis periods, allows for better quality in the rating process (Bar-Isaac and Shapiro, 2013). Additionally the event study methodology allows me to clearly quantify the effect of an increase in bank risk on sovereigns bonds while reducing endogeneity problems associated with the causality channel. To the extent that there is a risk transfer from the financial system to sovereigns, we should expected an increase in

[1]As a result from this situation regulators have been requested directly intervene banks' size (Huizinga and Demirgüç-Kunt, 2011; Millstein, 2011). Nevertheless this might not necessarily make them safer: many small banks can generate a deep crisis just as one large banks since the risk on their balances is in general more concentrated (Dewatripont, 2014)

spreads after a downgrade on a bank: Downgraded banks have higher default risk, increasing the need of potential bailouts (or other forms of government support). If these are financed with new debt, there would be a dilution on existing debt-holders, increasing their risk exposure.

Since this risk transfer is consistent with the idea of future bailout expectations (Dieckmann and Plank, 2012; Leonello, 2015), we can assess whether large banks are still regarded as *TBTF* by the market, or if some of them have become *TBTS*. If markets consider that some of the larger banks are not supported by governments anymore i.e. they are *TBTS*, the effect on spreads should not be significantly larger for bigger banks (since the bank is not expected to receive a bailout, sovereign debt levels should not change as much). On the other hand if larger banks are still deemed as*TBTF*, downgrades on these banks would have a stronger effect on sovereigns (Dieckmann and Plank, 2012; Acharya et al., 2014).

The evidence from the event study suggests a significant risk transfer from banks to sovereigns. The average immediate increase in daily sovereign spreads after a downgrade is about 2.11 basis points -bps- (for the Euro-area countries in the sample). Splitting downgrades between those leading to speculative grades or that deepens the bank into this category (i.e. high risk downgrades), and those in which the bank remains within investment grade category (i.e. low risk downgrades), modify the main results. Low risk downgrades do not imply a statistically significant change in spreads (less than 1 bps), i.e. there is little risk transfer in this cases. But for high risk downgrades, the immediate average effect on the daily change of spread rises to 2.99 bps (for the Euro-area sample), i.e. there is a significant risk transfer. In general, each downgraded notch leads to an average increase in spreads of 1.3 bps. Whenever the downgrade takes place in a distressed economy, it leads to an additional increase (over non-distressed economies) of 2.04 bps on spreads, i.e. for distressed countries the risk-transfer means a more severe problem to the government. The main results and conclusions remain mostly unchanged after a battery of robustness checks.

Additionally, results suggest that creditors are, in general, expecting a bailout on downgraded banks. Furthermore, the expected value of being bailed out is more important for larger banks. Particularly, when a bank with systemic size of at least 50% is downgraded, there is an additional effect (over smaller banks) of 2.06 bps on spreads.[2] Setting this threshold at 100%, the additional effect on spreads raises about 2.32 bps. In general it seems that as the size of downgraded banks increases, the effect on spreads is significantly larger. These results are consistent with the idea that markets consider that large banks are still implicitly insured by governments. Nevertheless, analyzing downgrades of systemically large banks located in distressed economies, I find different results. The effect of downgrades to large banks located in GIIPS economies on spreads is lower that the average effect. Particularly if a downgrade (within speculative grades) on a large bank (systemic size larger than 100%) occurs in a distressed economy, there is a significantly lower impact on spreads. These elements are consistent with the idea that large banks located in distressed countries, might be considered as *TBTS*. Finally, I perform a cross-sectional analysis.The results confirm the finding that downgrades on larger banks induce a wider increase in spreads, while downgrades on systemically larger banks are less harmful in terms of risk transfer (even after controlling for other bank's characteristics). This analysis also allows to indirectly test for the existence of a 'Too Many to Fail' (*TMTF*) problem, when multiple downgrades on relatively small banks

[2] Following previous literature, banks' systemic size is measured as the ratio of bank's total liabilities to home country's GDP.

occur. Nevertheless I find no evidence that these multiple downgrades imply a larger risk transfer, at least for the sample used.

This paper contributes to the existing literature in several ways. First, using a novel approach I am able to confirm and quantify the degree of risk transfer from banks to sovereigns (Acharya et al., 2014). To the extent of my knowledge, this is the first paper that relates banks' rating downgrades to sovereign bond spreads, increasing our understanding on the relationship between the financial and the public sectors. The event study methodology allows me to reduce more severe endogeneity problems that other methodologies might have, while establishing a clearer causal link from banks to sovereigns. [3] An additional advantage of the methodology is the neat way to interpret the results in terms of changes in spreads. Another novel feature is the use of banks' standalone rating downgrades as a signal of increased default risk, a documented fact in the literature (Billett et al., 1998). Results complement the literature on the utility of credit ratings, and the information transmission to the markets (Afonso et al., 2012). Furthermore, the paper also contributes to the literature on implicit guarantees to the financial system (Bertay et al., 2013; Demirgüç-Kunt and Huizinga, 2013). Using an European sample poses several improvements: it allows for the existence of 'systemic banks' (a feature that a US sample might not permit) while preserving some heterogeneity as well.

The rest of the paper is organized as follows: Section 2 presents a literature review. Section 3 explains the methodology and data used. Section 4 presents the empirical results and section 5 concludes. In appendix A I present additional explanation on Bank Financial Strength Ratings. In appendix B some clarifications on data is presented, while the results of

[3]However we can not be sure that they are completely overcome as argued by Roberts and Whited (2012)

some unit-root tests are in appendix C. Finally appendix D, presents some supplementary tables with summary statistics and additional results from robustness analyses.

2.2 Literature Review

There are several recent papers explaining the close link between the financial and the public sector. Acharya and Rajan (2013) and Gennaioli et al. (2014) develop theoretical frameworks to analyze the reasons and consequences of sovereign debt holdings by banks. On a similar line Acharya and Steffen (2015) empirically find a *carry trade* behavior by banks, i.e. banks increased their long-term periphery sovereign holdings using short-term debt in order to increase profits.

Closely related to this paper, Acharya et al. (2014) and Leonello (2015) explain from a theoretical perspective the interplay between bank and sovereign risks. Government guarantees and bailout expectations arise as the main reason for this link. Additionally, Acharya et al. (2014) finds empirical evidence of this link analyzing the relationship between banks and sovereigns CDS spreads, before during and after the financial crisis. Analyzing sovereign CDS spreads and their relationship with the health of the financial sector, Dieckmann and Plank (2012) find evidence consistent with a risk transfer between banks and public sector arising due to bailout expectations.

These bailout expectation are closely related with the existence of implicit guarantees in the form of *TBTF* subsidies. There is a vast literature on these issues. O'Hara and Shaw (1990) use an event study and find that banks deemed as *TBTF* had a positive wealth effect when bailout expectations were increased.[4] Penas and Unal (2004) analyze bond price reaction to M&A announcements and find evidence consistent with the *TBTF* implicit insurance.

But this implicit insurance might be reduced if banks are considered *TBTS*. Allen et al. (2011a) argue that financially distressed governments might not be able to honor their guarantees for larger banks. Analyzing the relationship between banks' systemic size (*liabilities-to-GDP* ratio) and some market discipline measures, Bertay et al. (2013) find evidence for the *TBTS* situation. Similarly Demirgüç-Kunt and Huizinga (2013) find empirical support for the *TBTS* hypothesis when analyzing banks' equity prices (for the 1991-2008 period) and CDS spreads (for the 2001-2008 period). This problem is particularly severe for *systemically large* banks located in countries with poor fiscal balances.

Finally this paper is related to the use of rating downgrades. There are several studies that relate banks' ratings with market discipline and safety-nets. For instance Billett et al. (1998) use Moody's downgrades as a proxy for "*discrete changes in bank risk*", or Rime (2005) that analyzes ratings from Fitch and Moody's to assess if implicit insurance pushes banks' ratings upward. Morgan (2002) finds significant discrepancies between agencies' ratings for banks, given the inner opaqueness of the banking industry. With respect to ratings' explanatory power to predict sovereign yields, Afonso et al. (2012) find that downgrades on sovereigns lead to a significant increase in spreads. Additionally they find that ratings announcements are not anticipated on the previous months. Bar-Isaac and Shapiro (2013) develop a theoretical framework to explain that rating agencies release higher quality

[4] In 1984, after the bailout of Continental Illinois Bank, the comptroller of the currency (testifying at the Congress) admitted that if needed larger banks would be granted financial aid. On that session congressman McKinney admitted that "We have a new kind of bank. It is called too big to fail."

ratings (more accurate) during recession due to reputation issues.

2.3 Data and methodology

2.3.1 Data

I gather information for daily yields to redemption for 10 year sovereign bonds from Datastream. These yields are estimated using the price of a single underlying bond. Datastream uses a benchmark bond for this estimation that is reviewed each month. In general it is represented by the latest issue or the most representative one, within that maturity.

The sample period starts on January, 3^{rd} 2005, until December, 31^{st} 2013. Countries under analysis are shown in table 2.1. Following Afonso et al. (2012) I use German bond's yield to construct the spreads. Since German bonds are regarded as a 'safe haven' (Bernoth et al., 2012), they can be used as a 'risk-less' rate. Furthermore, it is useful to control for common shocks across countries. Due to currency exchange concerns, I analyze separately the subsample of euro-area countries. I end up with a panel of 23,460 country-day observations on the 'Full-Sample' and 18,768 for the 'Euro-Sample' (see the appendix for a summary statistics on these observations).

In the time period under analysis, banks were severely constrained increasing the value of government guarantees. Additionally some of these European countries were financially impaired, with high ratios of government debt to GDP and high borrowing costs. These elements limit governments ability to bailout banks, setting the proper environment for a *TBTS* situation to arise.

Using the research and ratings module from Moody's, I hand collected a series of 'Bank Financial Strength Rating' (*BFSR*) downgrades.[5] These are assessments on banks' intrinsic strengths, i.e. they do not consider any form of external support. These are the main inputs to obtain the final ratings banks (see appendix for additional information). Downgrades can be used as indicators of increasing risk for banks (Billett et al., 1998). I collected information on all downgrades for all registered banks within the set of countries in the sample, for the time period under analysis. I end up with 476 downgrades for 180 different banks (the appendix presents some statistics on these downgrades). There are 283 cases in which more than one bank is downgraded on a single day in the country, and only 193 cases in which the bank was the only one downgraded in the day (downgrades occur either for individual banks, or for a group of banks.). Then I end up with 253 events distributed across 10 countries: 193 with a single downgrade, and 60 with multiple downgrades. Table 2.1 presents the distribution of events by country.

Then I transform the standalone grade into a numeric variable (from $A = 1$, to $E = 13$) and classify downgrades according to it. There are cases in which a downgrade leads to a speculative grade, while others keep the bank within investment grades. Then I classify downgrades between '*investment*' or '*speculative*'. In 127 days, these downgrades led to a speculative grade, i.e. lower or equal than $D+$ (the standalone equivalent to a $ba1$ *all in-rating* for Moody's). Table 2.1 presents this information while table 2.2 shows some statistics on the downgrades (for additional information see the appendix).

In those cases with more than one downgrade in a single day (and within the same country), it will be classified as *investment* or *speculative* depending on the grade of the largest bank. If the grade of this bank is *speculative*,

[5]For the period under analysis, S&P did not provide standalone ratings, while Fitch's individual ratings were not as easily accessible as Moody's *BFSR*.

regardless of the rest of the banks' grades, the downgrade is classified as a *speculative* one. In the appendix I present the results for two different alternatives to classify the grade in these cases: using the simple mean of the grades for all downgraded banks on the day, or alternatively as the weighted average of the grades (using as coefficients the relative size of each bank). Table 2.1 presents a summary of the days with downgrades and *speculative* downgrades (using the three alternatives).

Accounting data for banks is from Bankscope. Since Moody's does not provide any standard code to identify banks, merging downgrades with accounting information followed a manual process. GDP data (needed to estimate banks' systemic size) comes from Eurostat.

Figure 2.2 presents the spreads for each individual country under analysis. From this figure it seems clear that these processes are not stationary. Using a unit-root test we can not reject the hypothesis that the variable, in levels, has a unit-root (see the appendix). For this reason I use the first difference of spreads.

2.3.2 Event study methodology and hypotheses

I use the event study methodology to test the effect of bank's downgrades on sovereigns. Additionally, I assess whether banks' size is an important factor. Finally, I also distinguish between troubled and more stable economies in the analysis.

When using the traditional event study methodology (Kothari and Warner, 2007), one has to estimate a market model using a *normal* time period (i.e. time period with no events). Then using this *estimated model*, we can assess the abnormal reaction for days in which there are events. Nevertheless, in this study I do not have enough observations to update the *estimated model* between event dates. For this reason I rely on the observed sovereign spreads, following the approach proposed by Ongena et al. (2003) and Afonso et al. (2012).

I use an autoregressive model of order one, using as dependent variable the change in 10 year sovereign spreads between the day of the event and the following day. The independent variable is the corresponding first lag. In order to account for the effect of the downgrades I a use dummy variable, which equals one on the day of the event and zero otherwise. This dummy captures the abnormal return on the corresponding day. Given the panel of data, it is possible to use country fixed effects to control for unobserved heterogeneity among countries. Additionally, I also introduce year fixed effects to account for unobserved variables affecting countries throughout time.

$$\Delta S_{i,t} = \alpha_i + y_t + \beta \Delta S_{i,t-1} + \sum_{k=-\tau}^{+\tau} \gamma_k \delta_{i,(t+k)} + \varepsilon_{i,t} \tag{2.1}$$

Where $\Delta S_{i,t}$ is the change on spreads for country *'i'*, between day *'t+1'* and *'t'*. The variable α_i stands for the country fixed effects, while y_t represents the year fixed effects. The variable $\delta_{i,(t+k)}$ is the event dummy that takes value one if there is an event in country *'i'*, on day *'t'*, with an event window of size *'k'*.[6] Finally $\epsilon_{i,t}$ is an error term assumed to be normally distributed with zero mean.

Using a set of additional dummy variables in the days that follow and precede the event, we get the cumulative abnormal returns (CAR) for the corresponding event window. For instance the CAR[-1,+1] is given by:

$$CAR_{i,t}\,(-1,+1) = \gamma_{i,-1} + \gamma_{i,0} + \gamma_{i,+1}$$

[6]The total effect for a particular day would be given by $\frac{\partial \Delta S}{\partial \delta} = \frac{\gamma_k}{1-\beta}$ where β is the coefficient for lagged change in spreads

To the extent that there exists a link between banks and the public sector, I expect that downgrades on banks' ratings will imply an increase in sovereign spreads consistent with a risk transfer.

H_{1a}: *Downgrades on BFSR lead to an increase in sovereign spreads. This is consistent with a risk transfer from the financial sector to the sovereigns.*

If this link arises due to implicit guarantees and bailout expectations, downgrades leaving banks in the 'verge of default' should imply a larger reaction. After all these banks are more likely to need of external support. In order to differentiate between *investment* and *speculative* downgrades I modify equation (2.1) to capture this difference:

$$\Delta S_{i,t} = \alpha_i + y_t + \beta \Delta S_{i,t-1} + \sum_{k=-\tau}^{+\tau} \gamma_k^I \delta_{i,(t+k)}^I + \sum_{k=-\tau}^{+\tau} \gamma_k^S \delta_{i,(t+k)}^S + \varepsilon_{i,t} \tag{2.2}$$

In this case $\delta_{i,(t+k)}^I$ represents the dummy variable that accounts for *investment* downgrades, while $\delta_{i,(t+k)}^S$ stands for the *speculative* downgrades variable. I expect that the effect on sovereigns, should be stronger when the downgrade leads to a *speculative* grade rating (or deepens the bank into it).

H_{1b}: *Downgrades on BFSR leading to speculative grade (or deepening banks into this category), have a higher impact on sovereign spreads. This means that the risk transfer is more significant when banks are regarded as riskier.*

Within the *speculative* grade downgrades, we are including two different cases. First, those cases in which the bank was downgraded from *investment* to a *non-investment* grade (at least D+ in terms of the *BFSR*). Additionally, it also includes downgrades for banks that were already within the *speculative* grade. For this reason I include an additional dummy variable (*First Spec.*, δ^{first}) that takes value one whenever the downgrade leads to a *speculative* grade from an *investment* grade, and zero otherwise.

The idea is to test whether *speculative* downgrades are different when they occur within the range of *speculative* grades compared to those cases in which the bank has just fallen into *speculative* grades. In the following equation, I capture the additional impact of falling into *speculative* grades:

$$\Delta S_{i,t} = \alpha_i + y_t + \beta \Delta S_{i,t-1} + \gamma^I \delta^I_{i,t} + \gamma^S \delta^S_{i,t} + \lambda \delta^{FS}_{i,t} + \varepsilon_{i,t} \tag{2.3}$$

2.3.3 Including the effect of size

If the relationship between financial and public sector is due to government guarantees, we should expect that larger banks (those implicitly insured by the *TBTF* subsidy) generate a deeper reaction on sovereigns. In order to assess market's perception on the *TBTF* hypothesis, I include the systemic size in the analysis. For this purpose I follow two different strategies:

- First, I include an additional term in equation (2.1): the interaction between the downgrade dummy and the size of the downgraded bank. Whenever there is more than one downgrade, I use the size of the largest bank.[7] If banks are regarded as *TBTF*, downgrades on larger banks should lead to a wider increase on sovereigns spreads.

- But the relationship between size and government support likelihood does not have to be linear. Then, following Demirgüç-Kunt and Huizinga (2013) I use a set of dummy variables to account for banks' size, i.e.

[7] As robustness, I use a different approach to measure the 'size' whenever there are multiple downgrades. I compute it as the average size among all downgraded banks. Final conclusions remain mostly unchanged. The appendix presents these results.

greater or equal than 10%, 25%, 50% and 100%. As before I interact these dummies with the downgrades dummies. If banks are deemed as *TBTF*, I expect that the effect on spreads is higher for larger banks.

Then I estimate the following equation:

$$\Delta S_{i,t} = \alpha_i + y_t + \beta \Delta S_{i,t-1} + \gamma \delta_{i,t} + \eta \delta_{i,t} size_{X\%} + \varepsilon_{i,t} \tag{2.4}$$

The variable $size_{X\%}$ represents the systemic size of the downgraded bank (either in level, or using the aforementioned thresholds). The value and direction of η in the following expression is the object of the analysis.

H_2: *BFSR downgrades on larger banks have a significantly stronger effect on sovereign spreads if markets consider that these banks are still implicitly insured. This is consistent with a risk transfer due to government guarantees.*

2.3.4 Distinguishing the effects on troubled economies

The risk transfer might be dependent on the financial health of the country. If governments are financially distressed the damage inflicted by banks' downgrades might be more severe, given their impaired situation. Then in order to assess the differential effect of downgrades for different economies I propose an alternative setting. In this environment I differentiate between *GIIPS* and *non-GIIPS* using a dummy variable.

$$\Delta S_{i,t} = \alpha_i + y_t + \beta \Delta S_{i,t-1} + \gamma \delta_{i,t} + \phi \delta_{i,t} GIIPS + \varepsilon_{i,t} \tag{2.5}$$

H_3: *Downgrades on BFSR to banks located in distressed economies, will have a larger impact on sovereigns.*

Nevertheless, distressed countries' bailout capacity might be impaired as well. This means that larger banks might be less likely to receive government support if needed, i.e. they might be simply *TBTS*. In this setting we are able to separate the effects of downgrades depending on the size of the bank as well as the economy in which the bank is located.

$$\begin{aligned}\Delta S_{i,t} =& \alpha_i + y_t + \beta \Delta S_{i,t-1} + \gamma \delta_{i,t} + \eta \delta_{i,t} size_{X\%} \\ &+ \phi \delta_{i,t} GIIPS + \varphi \delta_{i,t} size_{X\%} GIIPS + \varepsilon_{i,t}\end{aligned} \tag{2.6}$$

Then we can state some additional hypothesis:

H_4: *BFSR downgrades on systemically larger banks located in distressed economies, will have a lower impact on sovereigns if banks are regarded as TBTS.*

2.3.5 Cross-sectional analysis

Additionally, I perform a cross section analysis similar to the traditional event study methodology (Kothari and Warner, 2007). In this setting I analyze how banks level characteristics are associated with the change in sovereign spreads after a downgrade, i.e. how these characteristics affect the risk transfer.

First, I estimate the abnormal change in spreads for each individual downgrade. In order to do this I create 253 dummy variables: one per day with event. The corresponding coefficient in the regression analysis will correspond to the abnormal change in spreads (AR), and will be the dependent variable in the cross-sectional analysis.

I use the following banks' characteristics to explain these ARs: size (measured as the natural logarithm of total assets), systemic size (measured as the total liabilities to GDP ratio), equity to total assets ratio (as presented in Bankscope), return on assets (as presented in Bankscope), and the liquid assets to customer and short term funds ratio (as presented in Bankscope). [8] Dummy variables to distinguish *speculative* downgrades, and the number of downgraded notches are included as well.

Finally, I include an additional dummy to capture the effect of multiple downgrades on a single day. If many banks are downgraded on the same day, given the *TMTF* hypothesis, we would expect an increase in the abnormal change in spreads. But there are many cases in which there is a large bank within this group. Then in order to have an unbiased indicator (i.e. only *small* banks), the *TMTF* dummy equals one whenever there is more than one downgraded bank but none of them has a systemic size above 50%.[9] Alternatively, I use a different dummy ($TMTF_{alt}$) that equals one whenever there is more than one downgrade but the sum of the sizes of all downgraded banks is lower than 50%.

The cross section analysis allows me to assess if there is a *TBTF* subsidy (examining the effect of size), if banks have become *TBTS* (analyzing the effect of systemic size), and if there is a *TMTF* situation (evaluating the corresponding dummy). This is estimated using a simple OLS with year and country fixed effects, where $AR_{i,t}$ is the abnormal change in spread generated by a downgrade on bank i in day t.

[8] For those cases in which more than one downgrade takes place in the same country-day, I use the accounting information from the largest bank.

[9] Conclusions hold for different thresholds, i.e. 25% and 10%. These cases are not tabulated.

$$
\begin{aligned}
AR_{i,t} =& \alpha_i + y_t + \beta \, Size_{i,t} + \gamma \, Sys.Size_{i,t} + \delta \, Equity_{i,t} + \eta \, ROAA_{i,t} \\
&+ \vartheta \, Liq_{i,t} + \lambda \, TMTF_{i,t} + \mu \, Spec_{i,t} + \rho \, Notches_{i,t} + \varepsilon_{i,t}
\end{aligned}
\tag{2.7}
$$

2.4 Empirical results

2.4.1 Effect of downgrades on sovereign

Figure 2.3 shows the average effect of downgrades on the change in spreads around the event date (for the *Full* and *Euro* samples). In general it seems that there is an increase in the spreads after a downgrade.

I proceed with the regression analysis as stated in equation (2.1), using all downgrades to *BFSR* in the *Full* sample, to assess their effect on the change in spreads. Then I consider only the subsample of *Euro* countries. Results are presented in Table 2.3 columns *(1)* and *(2)*. The variable of interest, *Downgrades*, has the expected sign and it is significant both in statistical terms (at a 10% level), and in economic terms as well (when considering the *Full* sample). The estimated coefficient for a downgrade is 0.0144%. Considering that the mean daily change in spreads is (for all statistical purposes) zero, the effect of the downgrade is economically important. Analyzing the *Euro* sample, I find that the variable of interest is larger and displays a higher statistical significance (5% level). The coefficient for the change in spread is 0.019% (almost 2 bps) on the day following the announcement.

Note that the full effect of *downgrades* is actually given by the expression $\frac{\gamma_{i,k}}{1-\beta}$. Then, the total effect of downgrades on spreads is around 1.6 bps for the *Full* sample and 2.11 bps for the *Euro* sample. Then downgrades on

BFSR lead to an increase in sovereign spreads as expected.

Results suggest that hypothesis H_{1a} is fully supported analyzing both the *Full* sample or the *Euro* sample. It is worth mentioning that the time period under analysis is characterized by high volatility (the main reason to use time fixed effects). Winsorizing data to reduce the effect of spurious outliers would yield similar results (presented in a subsequent subsection).

As previously commented, some of these downgrades leave banks withing *investment* grades, e.g. from A to $A-$. In these cases the bank is still a in a strong position. It is reasonable that banks within *investment* grades do not cause an important impact on sovereign spreads, i.e. since banks' risk of default is low the contagion (or risk transfer) effect to governments should be low as well. A bank that is in a solid position is less likely to need financial support by the government. For this reason in equation (2.2), I separate the downgrades into two different groups: those in which the institution remains within *investment* grades, and the rest in which the downgrade leads to a *speculative* grade category.

Figures 2.5(a) and 2.5(b) present the average effect on the change in spreads, only for *speculative* downgrades (using the *Full* and *Euro* samples respectively). Like before, it seems that after a *speculative* downgrade there is a significant increase in spreads.

Table 2.3 columns *(3)* and *(4)* present the results corresponding to the estimation of equation (2.2) for the *Full* and *Euro* samples respectively. The difference in behavior between *investment* and *speculative* downgrades, is evident. When analyzing the *Full* sample, the effect of downgrades for institutions with investment grades is not significant and the coefficient is economically small. If we examine speculative downgrades, the coefficient is more important in economic terms (2.34 bps) as well as in statistical terms (significant at a 5% level). When analyzing the *Euro* sample previous conclusions hold. The coefficient of *investment* downgrades is not statistically significant (nor economically important), while the coefficient for *speculative* downgrades is economically meaningful (a daily increase of 0.0269%) and statistically significant (at a 5%).

Again the full effect on spreads is given by the expression $\frac{\gamma_{i,k}}{1-\beta}$, so that *investment* downgrades imply an increase of 0.96 bps, while *speculative* downgrades imply an increase of 2.99 bps on spreads. This effect in daily spread changes is economically important.

There is a differential effect for downgrades depending on the final grade of the bank. The effect is more important when downgrades lead to a *speculative* grade (or deepens this status). The riskier the bank the larger the risk transfer to the sovereigns, as it was expected.

It is worth analyzing two different alternative approaches to assess the effect of downgrades. In Table 2.3 columns *(5)* to *(8)* present the results using two alternative variables instead if the downgrade dummy. First, *Numeric Grade* is a numerical transformation for the final grade, where the highest grade (A) corresponds to the lowest number (1). Second, *Downgraded Notches*, that is the number of notches that were downgraded for the corresponding bank. For the first variable (columns *(5)* and *(6)*), the worse the final grade (high numeric value) the higher the increase in sovereign spreads. This reaction in sovereigns is statistically significant at a 5% (considering both the *Full* and *Euro* samples). Additionally, the deeper the downgrade (more downgraded notches) the higher the effect on sovereigns. This relationship (significant at a 5%) suggests that for each downgraded notch there is an increase in spreads of 0.93 bps and 1.3 bps for the *Full* and *Euro* samples respectively.

Finally recall that *speculative* downgrades cover two possible cases: the bank is already within *speculative* grades and the downgrade deepens this situation; or the bank is within *investment* grades and the downgrade leaves the bank in a *non-investment* grade. Equation (2.3) separates these effects and Table 2.3 columns *(9)* and *(10)* present the results for the *Full* and *Euro* sample respectively. The additional dummy for *first time speculative* ($\delta_{i,t}^{FS}$) has a positive coefficient. Nevertheless, this additional effect is not different from zero in statistical terms. Then the differential effect of becoming a *speculative* grade bank is not an important factor driving the results.

In general these findings support the idea that downgrades on banks financial strength (a proxy for an increase in banks' risk) have a substantial effect on sovereign spreads (a significant risk transfer). When analyzing downgrades within the range of speculative grades, the effect becomes significantly larger. These findings are also supported when considering the final grade after the downgrade, or the number of downgraded notches. All these findings provide a strong support for hypotheses H_{1a} and H_{1b} (irrespective of the sample used). The evidence is consistent with a significant risk transfer from banks to governments whenever banks' default risk is increased.

Robustness - Analyzing alternative event windows

I extend the analysis assessing the cumulative abnormal returns for a wider set of event windows: 3-day CAR (t-1, t+1) and 7-day CAR (t-3, t+3).[10] Results are presented on the appendix.

The 3-days CAR shows that the effect of *investment* downgrades is not statistically different from zero (both for the *Full* and *Euro* samples). When analyzing *speculative* downgrades the 3-days CAR is 3.46 bps (significant at

[10] I analyze the 11-day CAR (t-5, t+5) as well and find that the effect of the events is not significant. Results are not tabulated.

a 5% level) and 4.36 bps (significant at a 5 %) for the *Full* and *Euro* samples respectively.

In the very short term around the event day, the effect of an *investment* downgrade is irrelevant for spreads. Nevertheless, for *speculative* downgrades the effect is very important, consistent with a significant risk transfer in the short-run.

For the 7-days CAR analysis, *investment* and *speculative* downgrades (using the *Full* and *Euro* samples) are not significant (statistically or economically).

The evidence shows that the abnormal effect of a downgrade on sovereigns is concentrated around the event date, i.e. it is not distributed throughout a long period of time. The abnormal reaction of sovereigns is short-lived, and disappears when analyzing wider event windows.

Robustness - Alternative classification for speculative grade

I introduce two alternative ways to distinct *speculative* from *investment* downgrades when more than one bank is downgraded. Instead of considering the grade of the largest bank (first definition), I use the average grade of all downgraded banks in that day (second definition) or alternatively the weighted average grade with weights dependent on bank' size (third definition). Results are presented on the appendix.

All previous conclusions remain mostly unchanged regardless of the definition used to define *speculative* downgrades. The effect that of downgrades leading to *speculative* grades remains significant for all the possible cases, and with similar coefficients. For this reason, throughout the rest of the analysis I will use the first *speculative* grade definition.

2.4.2 The effect of banks' size

In order to further analyze the hypothesis that there is a risk transfer due to government guarantees or implicit bailout expectations, I include the size of the downgraded bank in the analysis as in equation (2.4).

First, I proceed to analyze the effect of size in a linear way interacting bank' systemic size (liabilities-to-GDP ratio) with the downgrade dummy. If the *TBTF* hypothesis holds I expect that downgrades on larger banks will lead to larger increases on sovereign spreads. On the other hand, if the *TBTS* hypothesis holds, we should find a low non-significant (or even negative) coefficient.

Table 2.4 column *(1)* presents the results for the *Full* sample. Downgrades on larger banks lead to a larger increase in spreads. On the other hand, results from the *Euro* sample show that even though the coefficient of interest (the interaction term) is larger than before, it is not statistically significant (column *(2)*).

Then I split downgrades between *investment* and *speculative* grades. In this case only *investment* downgrades are significant for large banks (analyzing the *Full* sample). Surprisingly, *speculative* downgrades on larger banks do not have a statistically significant effect on spreads (even if this is economically large).

Table 2.4 in columns *(3)* and *(4)* summarizes these results (for the *Full* and *Euro* samples respectively). The evidence regarding the effect of bank' size on sovereigns and market's perception on potential bailouts is mixed.

Nevertheless, it might be the case that the effect is not linear. In order to test for this non-linearities regarding the effect of size, I create four set of dummies for the systemic size (similar to Demirgüç-Kunt and Huizinga 2013). Variables Size 10%, 25%, 50% and 100% equal 1 if the systemic size of the downgraded bank is greater or equal than the corresponding percentage. If there is more than one downgrade, I consider the size the largest bank (I explore a different alternative as robustness). Using this methodology we are able to disentangle the effect caused by larger banks as opposed to smaller ones with a non-linear setting.

Table 2.5 presents this information. It is straightforward that the additional effect of being systemically large is important. Note that as we increase the size of the downgraded bank the additional effect on sovereigns is larger in economic terms. In fact when the bank is sufficiently large, the effect becomes statistically significant. For the *Full* sample, banks with 50% or 100% *systemic size* (columns *5* and *7*) present an additional effect of magnitude 1.86 and 2.09 bps (significant at the 10% and the 1%) respectively. This supports the idea that downgrades on large banks generate a wider increase in spreads, consistent with the idea that larger banks are in general supported by the implicit governments' guarantees. Analyzing the *Euro* sample leads to the same conclusion. In this case when introducing the size dummies for 50% and 100% the effect is statistically and economically significant again (columns *6* and *8* from Table 2.5): downgrades on larger banks lead to a significantly larger increase in spreads. Particularly, the additional effect on sovereign spreads for downgrades on banks with *systemic size* larger than 50% is 2.41 bps (significant at a 5%). For the case of banks with *systemic size* larger than 100%, there is an extra increase of 2.42 bps on sovereign spreads (significant at a 5%). These results are consistent with the idea that larger banks are deemed as *TBTF*. Markets seem to be discounting a bailout to these larger banks (due to an implicit insurance), which in turn reflects a risk transfer from banks to governments.

As before I divide downgrades between *speculative* and *investment*. Table

2.6 present the corresponding results for the *Full* and *Euro* samples. For the *Full* sample (odd columns) increasing the size of the downgraded bank leads to a higher increase in spreads. For *speculative* downgrades, the additional effect is statistically significant when the bank has a *systemic size* larger than 50% (column *5*). This effect is 5.9 bps and significant at a 1% level. Surprisingly, for *speculative* downgrades on banks with *systemic size* larger than 100% the effect is not statistically significant (column *7*). Nevertheless, for these set of *systemically large* banks, the additional effect of *investment* downgrades is statistically significant. If we turn our attention to the *Euro* sample the main conclusions do not change. The additional effect for *speculative* downgrades when the bank has a *systemic size* larger than 50% is 5.95 bps (significant at a 1%). As before, when the downgrade (*investment* or *speculative*) occurs on banks with *systemic size* over 100% the additional effect is not statistically significant, though the coefficient is economically large.

These results are consistent with the *TBTF* hypothesis, while leaving some room for the existence of *too-big-to-rescue* banks. In general downgrades on larger banks have indeed a more important effect on spreads. This means that markets are discounting a potential bailout from governments to larger banks. Nevertheless, these findings do not rule out the existence of *TBTS* banks, i.e. the expected bailout for *systemically large* banks might not be larger for the bigger banks (as is the case in Table 2.6). In fact there is evidence consistent with this hypothesis as well.

With the evidence gathered, I can not reject hypothesis H_2. The effect on sovereign spreads of downgrades on large banks is significantly larger (compared to the average effect). This supports the idea that the risk transfer from large banks to governments, is significantly larger compared to the transfer conveyed by smaller banks. This result is consistent with the idea that markets are still expecting bailouts for these banks.

Robustness - Different definitions for size

When creating the size dummies with the four different thresholds, I considered the size of the largest downgraded bank during that day (if more than one downgrade took place on the corresponding date). As an alternative, I consider the average size of all the banks that were downgraded on that particular date.[11]

Results for the *Euro* sample are provided in the appendix.[12] Whenever a downgrades occurs the larger the average size of the downgraded banks, the greater the change in spreads. As before, this additional effect is statistically significant using size dummies for 50% and 100%. Splitting downgrades between *investment* and *speculative* leads to the same conclusions as with the first definition for size.

It is clear that using a different way to compute size thresholds does not change the major conclusions: downgrades on larger banks generate a wider increase in sovereign spreads.

2.4.3 The financial situation of the country

An important factor in the analysis (particularly to assess if banks are deemed as *TBTS*) is whether the country under consideration is financially distressed. I explicitly incorporate this into the regression analysis to assess whether there is a differential reaction for troubled economies.

[11] I use a third alternative, i.e. the weighted average size. Results are qualitatively the same as the simple mean, hence they are not tabulated.

[12] Analyzing the *Full* sample leads to the same conclusions.

I include an additional dummy in the regression to account for two different set of countries: troubled economies (Greece, Ireland, Italy, Portugal and Spain - GIIPS), and sounder economies (Belgium, France, Netherlands, Switzerland and UK). This dummy is interacted with the downgrade dummy as stated in equation (2.5). Table 2.7 presents these results for the *Euro* sample.[13]

First, note that the *downgrade* and the *speculative* grade dummies are significant regardless of the country. Analyzing the interaction terms between the *GIIPS* variable and the dummy *downgrades* (column *1*), leads to the conclusion that the effect on spreads is significantly larger for troubled economies (1.84 additional bps). Then I separate downgrades between *speculative* and *investment* (column *2*). The additional effect for riskier downgrades in *GIIPS* is not statistically significant. On the other hand, the additional effect of *investment* downgrades on *GIIPS* is statistically significant. This means that riskier downgrades do not have an additional effect on troubled economies (probably because the government is unable to completely insure the bank), while the opposite holds for less risky downgrades.

The evidence supports the idea that downgrades on banks located on distressed economies have a larger impact on sovereigns. This is consistent with the claim that the risk transfer from banks to governments is larger in troubled countries, supporting hypothesis H_3.

Then, I include the previous *systemic size* thresholds in the analysis in order to assess the effect of banks' size in distressed economies. This is presented in equation (2.6). According to the *TBTS* banks hypothesis, the effect of downgrades on larger banks should be less important for troubled economies since they are less likely to be able to bail out banks. Table 2.8

[13] Analyzing the *Full* sample does not qualitatively affect the main conclusions.

presents the main results using the *Euro* sample.[14]

First, note that the effect of downgrades is significant regardless of the size of the bank and the economy in which it is located (columns *1* to *4*). Then note that downgrades occurring on troubled countries imply a significant incremental effect. This means that the risk transfer from banks to sovereigns is larger when the economy is under severe distress (confirming the previous result and further supporting hypothesis H_3). Regarding banks size, it seems that as we increase the size threshold under analysis (from 10% to 100% in columns *1* to *4*), the effect of downgrades becomes larger and ultimately significant (for size 100%). These results are consistent with the idea that banks are still deemed as *TBTF*, and any potential bailout would further weaken countries' financial situation. But note that the *additional* effect of downgrades on large banks located in troubled economies is negative, although is not statistically significant.

Finally I split downgrades between *investment* and *speculative* (columns *5* to *8*). First of all note again, that the general effect of *speculative* downgrades is significant regardless of the size and location of the bank. As in the previous analysis (Table 2.7), the effect of downgrades on *GIIPS* is only significant for *investment* grade downgrades. As we increase the size of the downgraded bank, the effect becomes larger and significant for *speculative* downgrades. Note that the coefficients for the 25%, 50% and 100% size interactions (columns *6* to *8*) are significant and economically important. For instance, the additional effect of *speculative* downgrades on banks with *systemic size* larger than 50% and 100% is 8.84 and 14 bps respectively (columns *7* and *8*). Nevertheless, the additional effect for large banks that are located in troubled economies is negative and significant. Particularly the additional

[14]The analysis of the *Full* sample leads to similar conclusions.

effect of *speculative* downgrades on banks with size 50% and 100% in troubled economies is -4.03 and -15.59 bps respectively. This means that riskier downgrades on larger banks located in troubled economies are not as harmful for sovereigns, i.e. the risk transfer is lower in these cases. This is consistent with the idea that larger banks are regarded as *TBTS*, providing empirical support for hypothesis H_4. It seems that riskier downgrades on larger banks located in troubled economies do not imply a important risk transfer to sovereigns. These banks are (at best) partially insured, since the public sector is financially distressed.

2.4.4 Cross sectional analysis

I conclude the main analysis with the cross sectional study that is common across event studies. I estimate the abnormal change on spreads for each individual downgrade. For this procedure I re-estimate equation (2.1), but using one dummy per downgrade. The estimation is done using day fixed effects. The individual reactions for each downgrade generates a vector with 253 elements, that represents the new dependent variable in the cross section analysis. Then I proceed with the estimation of the coefficients as presented above in equation (2.7). Table 2.9 presents the results for the univariate analysis in column *(1)* and the multivariate analysis in columns *(2)* and *(3)*.

I will focus on three main findings here. First, note that the coefficient for *size* is positive and statistically significant. This is a clear indication that downgrades on larger banks generate a significantly larger reaction on sovereign spreads. This is consistent with the *TBTF* hypothesis. Additionally, note that the coefficient for the *systemic size* is negative and significant as well. This reaction is consistent with the *TBTS* idea, i.e. downgrades on *systemically larger* banks would imply a lower effect on sovereigns since the implicit insurance for these banks is lower. Finally the coefficient for the *TMTF* is negative and significant (both alternatives). This means that there is no evidence that multiple downgrades on relatively smaller banks generate a deeper risk transfer to sovereigns.

This cross section analysis provides evidence consistent with a risk transfer from banks to sovereigns due to government guarantees. Larger banks, that are implicitly insured (*TBTF*) imply a higher transfer, since the guarantees to these banks are larger. But if these banks become *systemically large*, they are deemed as *TBTS* and part of this implicit insurance is lost. Then, risk transfer in these cases is lower.

2.4.5 Additional analyses

The period under consideration suffers from large volatility since it covers the last financial crisis (this is one of the reasons for the low *adjusted R-squared* in all previous analysis). In order to prevent spurious inferences due to extreme outliers, I winsorize the data on the change of spreads at a 1% (for each tail). Given the nature of the experiment conducted, some extreme values might be caused by the events under analysis. For this reason, as an additional approach, I winsorize only values in non-event days (or surrounding dates). Since results are qualitatively and quantitatively similar, I only report the results for the first approach in the appendix.

When winsorizing data, all previous results and conclusions regarding the hypotheses analyzed are almost unchanged. The coefficients for event dummies and interactions (when considering size) as well as the corresponding significance levels, are in general slightly lower compared to the original analysis. But the magnitudes are not substantially different in statistical nor economic terms.

In order to assess the strength of the results regarding the risk transfer I repeat the analysis from equations (2.1) and (2.2) using day fixed effects. This allows me to capture changes in macroeconomic fundamentals and other unobserved shocks that might be affecting sovereign spreads (Acharya et al., 2014). Results for general downgrades and separating *speculative* from *investment* grade downgrades are tabulated in the appendix (using the *Full* and *Euro* samples). Using this approach the significance for all the coefficients is lower (as expected). Nevertheless, *speculative* downgrades still imply a significant increase in sovereign spreads, enhancing the validity of all previous conclusions. There is indeed an important risk transfer from the financial sector to sovereigns.

Finally, I include an additional variable into the analysis that captures the common movement within each country. The reason is to capture unobserved elements that might be driving both the changes in sovereign spreads as well as the decisions to downgrade banks. For this purpose I use the corresponding stock market benchmark index for each country under analysis. This is included throughout all the equations used, leading to quantitative and qualitatively similar results. Some of these results are tabulated in the appendix (using only the *Euro* sample). [15] These results strengthen the conclusions regarding bailout expectations and implicit insurance.

2.5 Conclusions

In this paper I use the event study methodology to analyze the relationship between downgrades on *banks financial strength ratings* and sovereign spreads. This analysis allows me to estimate and quantify the shift of risk

[15] The rest of the tables are available upon request.

from banks to governments. One of the main advantages of this methodology lies on the simplicity to interpret the results, while allowing to reduce endogeneity issues caused by reverse causality.

A priori, we would expect that riskier banking systems are related to higher sovereign spreads due to government guarantees. Results confirm this premise: increasing banks' risk (proxied by *BFSR* downgrades) translates into higher sovereign spreads. The evidence in this paper suggests that this risk transfer is mainly due to bailout expectations on banks, consistent with the findings by Leonello (2015), Acharya et al. (2014) and Dieckmann and Plank (2012). Distinguishing these events between downgrades within *investment* and *speculative* grades strengthens this explanation. Banks with a *speculative* grade are deemed as riskier, i.e. closer to default. In this context these type of downgrades generate a significantly larger reaction on sovereigns. This means that the risk transfer to sovereign spreads is particularly acute for riskier banks.

Then I introduce banks' *systemic size* into the analysis to test whether larger banks generate a wider effect. If large banks are deemed as *TBTF*, a larger effect on spreads would be consistent with a risk transfer due to government guarantees (bailout expectations). Results suggest that in general, downgrades on larger banks generate a significantly larger increase in sovereign spreads. This result supports the claim that larger banks are still regarded as *TBTF*. Additionally, this result is consistent with the idea that the risk transfer occurs because of the existence of government guarantees. Differentiating whether the downgrade occur in a troubled economy, I find evidence consistent with the idea that some banks are regarded as *TBTS*. Riskier downgrades on larger banks located in distressed economies generate a significantly lower reaction (as compared to downgrades on large banks located in more stable economies). The implicit insurance dilutes as governments are financially distressed, reducing the corresponding risk transfer.

Finally, I analyzed the cross section for the abnormal changes in spreads. This test confirmed previous results, i.e. larger banks generate a wider increase in spreads (*TBTF*), but there is evidence of *TBTS* situations as well.

These results and conclusions are robust to a set of additional tests and the use of different variables. The set of events chosen might have been (at least partially) anticipated by the market, i.e. the change in ratings for banks might be expected by the market. This means that the reaction I capture is actually a noisy signal of the event. Despite this additional noise the reaction I find is significant, strengthening the conclusions.

The contributions of paper are multiple. First, it complements in a novel way previous research regarding the link between the financial system and sovereigns' default risk, particularly the transfer from banks to sovereigns. The study provides additional empirical support for previous theoretical frameworks. Additionally, to the extent of my knowledge, this is the first paper to explicitly document the relationship between banks' downgrades and sovereign spreads. It also provides evidence on the use of ratings by the market to assess risk. The paper also allows to explicitly test if larger banks are still implicitly insured and whether some of them have become *TBTS*.

Since the evidence presented suggests that there is a risk transfer arising due to government guarantees, regulators should try to solve the usual moral hazard problem in order to reduce bailout expectations. Bail-in policies or reforming resolution regimes for large banks are some possible alternatives. Forcing banks to reduce their size may be tempting for distressed economies, and might help to reduce the potential risk transfer issue. Nevertheless it might not be the optimal way to deal with this problem since it will not take care of the distorted incentives in the banking sector. On the other hand, if bailout expectations are credibly reduced market discipline would be a more effective regulatory tool reducing bank risk-taking. In this case the corresponding risk transfer from banks to governments would be reduced as well. This would be true for two reasons: banks would be safer (there is less need for a bailout), and governments would be able to make credible commitments not to further bail out banks.

Tables

Table 2.1: Days with events by country

Market	**Downgrades**	**Speculative 1**	**Speculative 2**	**Speculative 3**
Belgium	13	4	4	4
France	32	14	16	15
Greece	9	6	7	6
Ireland	29	16	16	13
Italy	62	42	45	38
Netherlands	15	6	6	6
Portugal	16	14	15	11
Spain	27	13	14	13
Switzerland	15	0	0	0
UK	35	12	14	11
Total	**253**	**127**	**137**	**117**

Note: Speculative 1, 2 and 3 are defined according to the largest bank rating on that day, the mean rating, and the weighted average rating, respectively.

Table 2.2: Summary statistics - Grades & Notches

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Grade	476	8.75	2.48	2	1 3
Notches	476	1.53	0.85	1	6

Note: The mean grade lies between $C - /D+$, i.e. within investment grades.

Table 2.3: The effect of downgrades on sovereign spreads

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
$\Delta Spread_t$	0.0993***	0.1001***	0.0993***	0.1001***	0.0993***	0.1001***	0.0994***	0.1001***	0.0993***	0.1001***
Downgrades	0.0144*	0.0190**	-	-	-	-	-	-	-	-
Investment	-	-	0.0054	0.0086	-	-	-	-	0.0054	0.0086
Speculative	-	-	0.0234**	0.0269**	-	-	-	-	0.0227**	0.0233**
Num. grade	-	-	-	-	0.0018**	0.0022**	-	-	-	-
Notch downg.	-	-	-	-	-	-	0.0084**	0.0117**	-	-
First Spec.	-	-	-	-	-	-	-	-	0.0017	0.0094
Constant	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002
N	23450	18760	23450	18760	23450	18760	23450	18760	23450	18760
$Adj R^2$	0.0107	0.0111	0.0107	0.0111	0.0107	0.0111	0.0107	0.0111	0.0107	0.011

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Even columns include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *First Spec.* is a dummy that equals one if the final grade of the downgraded bank equals or is lower than D+ while the original grade (pre-downgrade) was above D+. *Num. grade* is a numerical transformation of the final grade of the downgraded bank, where the lower the grade the higher the numerical value (this variable equals zero if during the corresponding day, there is no downgrade). *Notch downg.* is a numerical value representing the amount of downgraded notches on the corresponding day for the downgraded bank. All regressions are using country and year fixed effects.

Table 2.4: The effect of downgrades on sovereign spreads: Linear relationship with size

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.0993***	0.1001***	0.0993***	0.1001***
Downgrade	0.0143*	0.0188**	-	-
Down. x Size	0.0091*	0.0131	-	-
Investment	-	-	0.0052	0.0083
Speculative	-	-	0.0233**	0.0269**
Spec. x Size	-	-	0.0389	0.04
Invest. x Size	-	-	0.0045*	0.0037
Constant	0.0001	0.0002	0.0001	0.0002
N	23450	18760	23450	18760
$AdjR^2$	0.0107	0.0111	0.0106	0.011

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Columns (2) and (4) include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *Size* is the systemic size of the bank as measured by the ratio of its total liabilities to its home country GDP. All regressions are using country and year fixed effects.

Table 2.5: The effect of downgrades on sovereign spreads: Non linear relationship with size

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\Delta Spread_t$	0.0993***	0.1001***	0.0993***	0.1001***	0.0993***	0.1001***	0.0993***	0.1001***
Downgrade	0.0143*	0.0188**	0.0144*	0.0188**	0.0144*	0.0189**	0.0144*	0.0189**
Down. x Size-10%	0.0069	0.0078	-	-	-	-	-	-
Down. x Size-25%	-	-	0.0062	0.0085	-	-	-	-
Down. x Size-50%	-	-	-	-	0.0186*	0.0241**	-	-
Down. x Size-100%	-	-	-	-	-	-	0.0209***	0.0242**
Constant	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002
N	23450	18760	23450	18760	23450	18760	23450	18760
$Adj R^2$	0.0107	0.0111	0.0107	0.0111	0.0107	0.0111	0.0107	0.0111

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Even columns include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. All regressions are using country and year fixed effects.

Table 2.6: The effect of downgrades on sovereign spreads: Non linear relationship with size - Investment vs Speculative

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\Delta Spread_t$	0.0994***	0.1001***	0.0994***	0.1001***	0.0993***	0.1001***	0.0993***	0.1001***
Investment	0.0052	0.0084	0.0052	0.0083	0.0054	0.0086	0.0053	0.0084
Speculative	0.0233**	0.0268**	0.0233**	0.0268**	0.0235**	0.0270**	0.0234**	0.0269**
Spec. x Size-10%	0.0163	0.017	-	-	-	-	-	-
Inv. x Size-10%	0.0015	0.0012	-	-	-	-	-	-
Spec. x Size-25%	-	-	0.0212	0.0223	-	-	-	-
Inv. x Size-25%	-	-	-0.0006	0.0006	-	-	-	-
Spec. x Size-50%	-	-	-	-	0.0590***	0.0595***	-	-
Inv. x Size-50%	-	-	-	-	0.0059	0.0089	-	-
Spec. x Size-100%	-	-	-	-	-	-	0.0472	0.0465
Inv. x Size-100%	-	-	-	-	-	-	0.0144*	0.0163
Constant	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002
N	23450	18760	23450	18760	23450	18760	23450	18760
$Adj R^2$	0.0106	0.011	0.0106	0.011	0.0107	0.011	0.0106	0.011

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Even columns include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above $X\%$, or zero otherwise. All regressions are using country and year fixed effects.

Table 2.7: The effect of downgrades on sovereign spreads: GIIPS

Variable	**(1)**	**(2)**
$\Delta Spread_t$	0.1001***	0.1001***
Downgrade	0.0061*	-
Down. x GIIPS	0.0184*	-
Investment	-	-0.0025
Speculative	-	0.0189*
Spec. x GIIPS	-	0.0102
Inv. x GIIPS	-	0.0188***
Constant	0.0002	0.0002
N	18760	18760
$Adj R^2$	0.0111	0.011

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regressions include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *GIIPS* is a dummy that takes value 1 if the home country of the bank is a distressed economy (Greece, Ireland, Italy, Portugal or Spain), or zero otherwise. All regressions are using country and year fixed effects.

Table 2.8: The effect of downgrades on sovereign spreads: GIIPS and Size

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\Delta Spread_t$	0.1001***	0.1001***	0.1001***	0.1001***	0.1001***	0.1001***	0.1001***	0.1001***
Downgrade	0.0058*	0.0059**	0.0058**	0.0056**	-	-	-	-
Speculative	-	-	-	-	0.0191*	0.0190*	0.0190*	0.0190*
Investment	-	-	-	-	-0.0027	-0.0026	-0.0027	-0.0026
Down. x G.	0.0186*	0.0185*	0.0187*	0.0188*	-	-	-	-
Spec. x G.	-	-	-	-	0.01	0.01	0.0102	0.0101
Inv. x G.	-	-	-	-	0.0188***	0.0188***	0.0190***	0.0189***
Down. x Size	0.0124	0.0154	0.019	0.0284***	-	-	-	-
Down. x Size x G.	-0.0087	-0.0129	0.013	-0.009	-	-	-	-
Spec. x Size	-	-	-	-	0.0319	0.0563*	0.0884***	0.1400***
Spec. x Size x G.	-	-	-	-	-0.023	-0.0464	-0.0403***	-0.1559***
Inv. x Size	-	-	-	-	0.004	0.0046	0.0073	0.0044
Inv. x Size x G.	-	-	-	-	-0.0062	-0.0094	0.0068	0.0414***
Constant	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
N	18760	18760	18760	18760	18760	18760	18760	18760
$Adj R^2$	0.011	0.011	0.0111	0.011	0.0108	0.0108	0.0108	0.0108

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regressions include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *GIIPS* is a dummy that equals 1 if the home country of the bank is a distressed economy (Greece, Ireland, Italy, Portugal or Spain), or zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. For columns **(1)** and **(5)** this threshold is 10%, for columns **(2)** and **(6)** the threshold is 25%. In columns **(3)** and **(7)** the threshold is 50% and for columns **(4)** and **(8)** the threshold is 100%. All regressions are using country and year fixed effects.

Table 2.9: The effect of downgrades on sovereign spreads: Cross section analysis

Variable (AR)	**(1)**	**(2)**	**(3)**
Size	0.0006**	0.0113***	0.0104**
Systemic size	0.0131***	-0.0217*	-0.0207*
Equity ratio	0.0009*	0.0015	0.0013
$ROAA$	-0.0059	-0.0054	-0.0054
Liquidity ratio	0.0001	0.0000	0.0000
$TMTF$	0.0027	-0.0283**	-
$TMTF_alt$	-0.0166**	-	-0.0289**
Notches	0.0104**	0.0089	0.0083
Speculative	0.0158**	0.0161	0.0153
N	234	234	234
$AdjR^2$	-	0.1070	0.1035

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

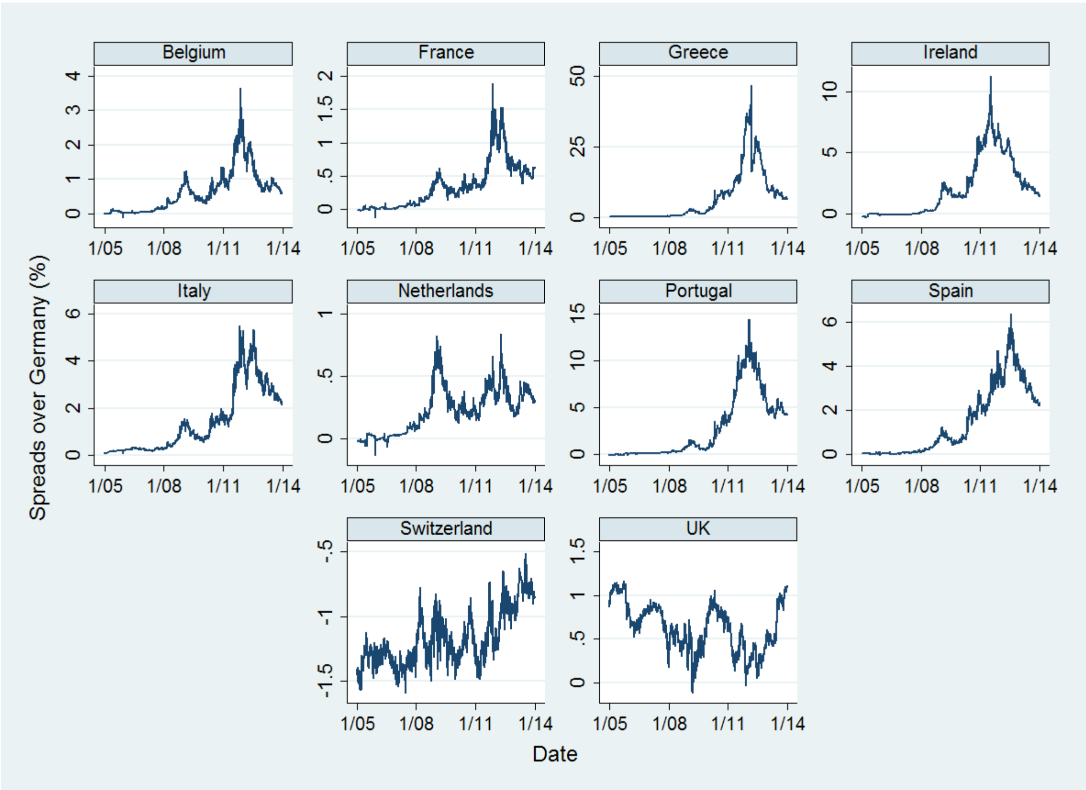
Note: Dependent variable is the abnormal change in sovereign spreads after the downgrade takes place (estimated using day and country fixed effects). *Size* is the natural logarithm of banks' total assets and *Systemic size* is the ratio between banks' total liabilities to country's GDP. *Equity ratio* is the equity to total assets ratio, $ROAA$ is the return on average assets (average between year t and $t-1$) and *Liquidity ratio* is the liquid assets to deposits and short-term fundings ratio. *TMTF* is a dummy variable that equals 1 if more than one downgrade takes place (on that day) and none of the downgraded banks is large (systemic size 50%), and zero otherwise. $TMTF_{alt}$ is a dummy variable that equals 1 if more than one downgrade takes place (on that day) and the sum of all downgraded banks' systemic size is lower than 50%, and zero otherwise. *Notches* corresponds to the number of downgraded notches, while *Speculative* is a dummy that equals 1 if the final grade of the downgraded bank is lower or equal than D+. Column **(1)** corresponds to the univariate analysis, while column **(2)** and **(3)** are multivariate analyses using country and year fixed effects.

Figures

Figure 2.1: Irish vs Icelandic CDS spreads

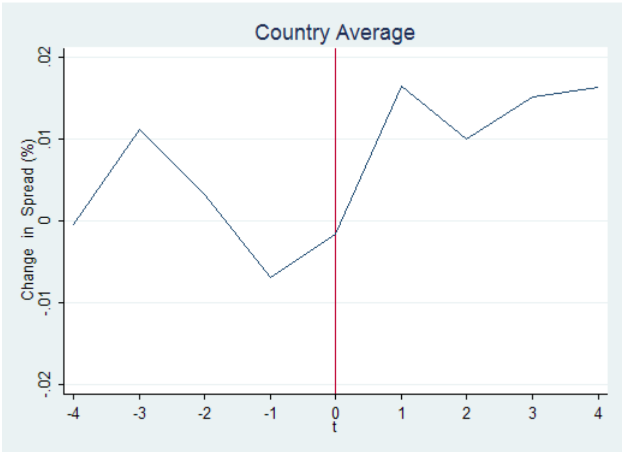
Note: Daily CDS spreads for Ireland and Iceland. Computed using 5-year contracts. Measured in basis points. On 30-09-2008 Ireland announced that deposits of all major banks were guaranteed (bailout line). On 06-10-2008 Iceland let major banks fail. Finally, on 08-03-2010 in the Iceland referendum to determine (among other things) whether to pay to foreign depositors (from UK and Netherlands), the “NO” won with 98%.

Figure 2.2: Spreads by Country

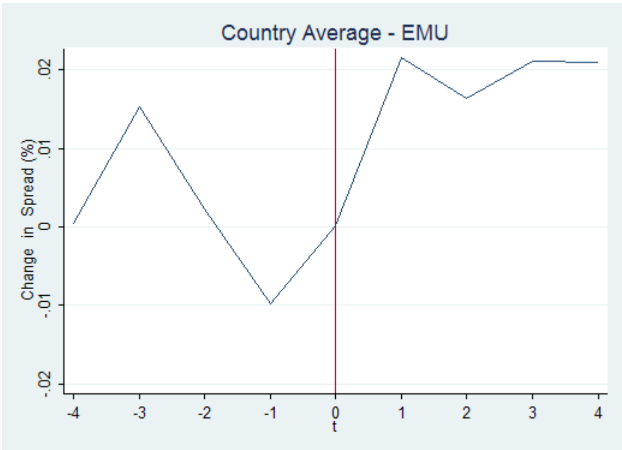


Note: Daily sovereign bond spread. Computed using 10-year bonds, and spreads over German bonds. Measured in percentage points. Sample period (horizontal axes) starts in January 2005, and finishes in December 2014.

Figure 2.3: Change in spreads - All downgrades - Mean effect



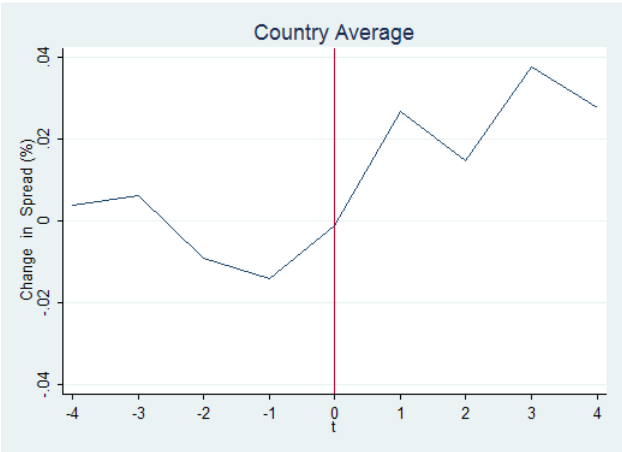
(a) Full sample



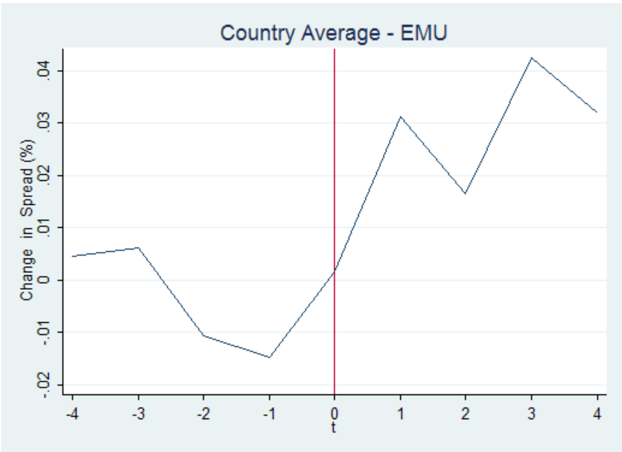
(b) Euro sample

Note: Change in spreads (measured in percentage points) around the event date, computed using all downgrades in the sample. Average effect across countries. Day $t = 0$ corresponds to the downgrade date.

Figure 2.4: Change in spreads - Speculative downgrades - Mean effect



(a) Full sample



(b) Euro sample

Note: Change in spreads (measured in percentage points) around the event date, computed using only *speculative* downgrades in the sample. Average effect across countries. Day $t = 0$ corresponds to the downgrade date.

Appendix A: Bank Financial Strength Rating

The *BFRS* is not a credit rating itself, but an assessment of "each bank's intrinsic, or standalone" strength. [16] Since it reflects the probability of default, it is related to the possibility of needing external support either by its owners or other official institution. It is an input to get the final rating of the banks.

The *BFRS* (that is based on 13 possible ratings from A to E) translates into a Baseline Credit Assessment (*BCA*):

BFSR to BCA conversion

BFSR	**BCA**	**Grade (if final rating)**
A	aaa	Investment
A-	aa1	Investment
B+	aa2	Investment
B	aa3	Investment
B-	a1	Investment
C+	a2	Investment
C	a3	Investment
C-	baa1	Investment
C-	baa2	Investment
D+	baa3	Investment
D+	ba1	Speculative
D	ba2	Speculative
D-	ba3	Speculative
E+	b1	Speculative
E+	b2	Speculative
E+	b3	Speculative
E	caa1	Speculative
E	caa2	Speculative
E	caa3	Speculative

Then taking into consideration external support factors (parent, local or national governments) or country ceilings, the final senior debt and deposit

[16] In order to obtain the set of *BFRS* downgrades, I used Moody's web page search module with the following parameters: 'Financial Institutions; Banking; Banks; Bank'.

rating is obtained.

To obtain the *BFRS*, Moody's consider 5 different intrinsic key factors. Using scorecards they evaluate each of the factors (and sub-factors), and assign scores that will translate into the final grade depending on the weight of each factor.

- Franchise Value: Market share and sustainability, geographical diversification, earnings stability and diversification.
- Risk positioning: Corporate governance, controls and risk management, financial reporting transparency, credit risk concentration, liquidity management, and market risk appetite.
- Regulatory Environment: Independence (of regulator), regulatory standards, supervision, enforcement, maturity of regulatory framework, and health of banking system.
- Operating Environment: Economic stability, integrity and corruption, and legal system. [17]
- Financial Fundamentals: Profitability, liquidity, capital adequacy, efficiency, and asset quality.

The first four are qualitative factors. The weights of each factor (financial fundamentals and qualitative component) will depend on the country in which the bank is located: whether it is a mature or a developing market. Moody's determines this using each country ceilings for sovereign bonds. [18] Those countries with a ceiling Aa1 or greater are considered mature markets. Given the sample of countries, Greece loses its Aaa ceiling on June, 1^{st} 2012

[17] The economic stability is measured using the standard deviation of GDP growth.
[18] Country ceilings should not be confused with government's credit ratings.

becoming Caa2. Ireland did so on September, 6^{th} 2012 with a A3 ceiling. Italy loses its Aaa category and becomes A2 on July, 13^{th} 2012. Portugal was downgraded on September, 5^{th} 2012 becoming Baa3. Finally Spain suffered a ceiling downgrade on June, 13^{th} 2012 and becomes A3. This means that throughout almost all sample time period all the countries under analysis are categorized as mature markets.

On mature markets both qualitative and financial fundamentals are equally weighted. On developing markets, qualitative factors represent 70% of the final score, while financial fundamentals stand for the remaining 30%. Additionally for mature markets franchise value and risk positioning represent 40% of the final qualitative score, while the operating and regulatory environment, represent only 10%. On the other hand in developing markets, franchise value represents 10% of the final qualitative score, while each of the remaining factors (risk positioning, regulatory and operating environment) represent 30% of the qualitative score.

Giving the nature of the analysis (the effect of downgrades in *BFRS* on sovereign bonds) one might be worried about reverse causality. For example a poor macroeconomic environment, might lead sovereign yields up, and bank ratings down. But given the low weights of these factors on the *BFRS*, this is a relatively unimportant factor (economic stability represents 7% of the final score in developing markets, and only 1.7% for mature markets). Similar situation applies when there is a downgrade on sovereign. The effect should be captured by the 'operating environment' factor, but the weight assigned to it might not be enough to lead the rating down.

On March 17^{th}, 2015 Moody's announced that for business reasons, the BFSRs were withdrawn as inputs to ratings. From that moment onwards only the BCA would indicate standalone ratings. [19]

Appendix B: Sovereign bond data

The information regarding sovereigns was obtained from Datastream using the following codes.

Datastream codes for Sovereigns

Name	Code
BELGIUM BENCHMARK BOND 10 YR (DS) - RED. YIELD	BGBRYLD
FRANCE BENCHMARK BOND 10 YR (DS) - RED. YIELD	FRBRYLD
GREECE BENCHMARK BOND 10 YR (DS) - RED. YIELD	GRBRYLD
IRELAND BENCHMARK BOND 10 YR (DS) - RED. YIELD	IRBRYLD
ITALY BENCHMARK BOND 10 YR (DS) - RED. YIELD	ITBRYLD
NETHERLANDS BENCHMARK BOND 10 YR (DS) - RED. YIELD	NLBRYLD
PORTUGAL BENCHMARK BOND 10 YR (DS) - RED. YIELD	PTBRYLD
SPAIN BENCHMARK BOND 10 YR (DS) - RED. YIELD	ESBRYLD
UK BENCHMARK BOND 10 YR (DS) - RED. YIELD	UKMBRYD
SWITZERLAND BNCHMRK. BOND 10 YR (DS) - RED. YIELD	SWBRYLD
GERMANY BENCHMARK BOND 10 YR (DS) - RED. YIELD	BDBRYLD

These series are copied from the previous "Benchmark 10 Year DS Govt." (e.g. for Belgium the alternative code would be: BMBG10Y). These series are based on single underlying bond which have 10 year life. This bond is the most representative available for the corresponding maturity, at that period of time. In general these benchmarks are the latest issue within the maturity band. Datastream reviews daily new bonds for the selection of the benchmark, and at the beginning of each month changes are made (if needed).

[19]See https://www.moodys.com/research/Moodys-reviews-global-bank-ratings--PR_321005.

Appendix C: Unit-Root test for yields and spreads

In order to complement the plots for the spreads for each individual country, I present the Levin-Lin-Chu test to evaluate whether spreads (and the change in daily spreads) have unit-roots. The null hypothesis is the presence of a unit-root in the series.

Levin-Lin-Chu unit-root test for spread

Ho: Panels contain unit roots	Number of panels =	10
Ha: Panels are stationary	Number of periods =	2347
	Statistic	**p-value**
Unadjusted t	-6.024	
Adjusted t*	0.1922	0.5762

Note: Estimated using 0 lags and a time trend.

It seems clear that there process is not stationary. The I estimate the differences in spreads and performed the same test.

Levin-Lin-Chu unit-root test for the change in spreads

Ho: Panels contain unit roots	Number of panels =	10
Ha: Panels are stationary	Number of periods =	2346
	Statistic	**p-value**
Unadjusted t	$-1.40E+02$	
Adjusted t*	$-2.40E+02$	0

Note: Estimated using 0 lags and a time trend.

There is no doubt, when analyzing the changes in spreads, that the series is stationary.

Appendix D: Additional summary statistics and tables

Table 2.10: Summary statistics - Daily change in spreads

Market	**N**	**Mean**	**Std.Dev**	**Min**	**Max**
$\Delta Spread$ (%) - Overall	23460	0.0008	0.2164	-27.446	7.03
$\Delta Spread$ (%) - Belgium	2,346	0.00026	0.04205	-0.29300	0.32400
$\Delta Spread$ (%) - France	2,346	0.00027	0.02826	-0.28700	0.27200
$\Delta Spread$ (%) - Greece	2,346	0.00274	0.65277	-27.44600	7.03000
$\Delta Spread$ (%) - Ireland	2,346	0.00073	0.09114	-1.21270	0.82300
$\Delta Spread$ (%) - Italy	2,346	0.00087	0.07479	-0.77500	0.59500
$\Delta Spread$ (%) - Netherlands	2,346	0.00013	0.01790	-0.12300	0.15300
$\Delta Spread$ (%) - Portugal	2,346	0.00182	0.13170	-1.65460	1.75900
$\Delta Spread$ (%) - Spain	2,346	0.00093	0.07469	-0.81800	0.43000
$\Delta Spread$ (%) - Switzerland	2,346	0.00024	0.03839	-0.25220	0.17200
$\Delta Spread$ (%) - UK	2,346	0.00006	0.03235	-0.23690	0.23620

Table 2.11: Downgrades by country-year

Market \ Year	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**Total**
Belgium	4	4	3	-	3	3	-	*17*
France	13	4	10	2	7	13	3	*52*
Greece	-	-	9	11	11	-	-	*31*
Ireland	6	5	19	4	1	7	4	*46*
Italy	21	5	18	6	9	32	19	*110*
Netherlands	4	1	6	3	2	3	1	*20*
Portugal	6	3	9	3	10	8	1	*40*
Spain	15	9	24	-	3	29	8	*88*
Switzerland	5	4	1	-	2	6	2	*20*
UK	11	7	21	1	-	8	4	*52*
Total	**85**	**42**	**120**	**30**	**48**	**109**	**42**	**476**

Table 2.12: Summary - Downgrades characteristics by country

Market	Grade		Notches	
	Mean	SD	Mean	SD
Belgium	7.235	1.855	1.235	0.562
France	8.115	2.211	1.423	0.977
Greece	10.742	2.016	1.419	0.564
Ireland	9.022	2.736	1.717	1.047
Italy	9.427	1.960	1.464	0.738
Netherlands	7.700	2.618	1.400	0.821
Portugal	9.850	2.143	1.400	0.672
Spain	8.875	2.453	1.761	0.935
Switzerland	6.450	1.538	1.400	0.754
UK	7.269	2.521	1.615	0.932
Total	**8.752**	**2.476**	**1.534**	**0.852**

Table 2.13: Number of (different) downgraded banks by country

Market	Number
Belgium	4
France	18
Greece	9
Ireland	15
Italy	47
Netherlands	9
Portugal	10
Spain	39
Switzerland	11
UK	18
Total	**180**

Table 2.14: Number of banks by specialization

Specialization	Number
Commercial, coop. and saving	148
Investment and private	13
Real estate and gov. credit inst.	10
Finance companies	6
Bank holding companies	3
Total	**180**

Table 2.15: Characteristics of downgraded banks: by country

Market	**Log(TotAssets)**	**Sys. Size**	$\frac{Equity}{TotAssets}$	**ROAA**	$\frac{Liq.Asset}{Dep\&STFund}$
Belgium	20.03	1.11	3.59	-0.57	28.41
France	19.70	0.29	4.24	0.25	68.07
Greece	17.73	0.23	5.15	-3.67	10.93
Ireland	18.12	0.52	6.38	-1.40	31.67
Italy	17.33	0.06	6.74	-0.28	22.93
Netherlands	19.03	0.61	4.14	0.05	38.65
Portugal	17.86	0.32	2.43	-0.60	17.92
Spain	17.86	0.12	5.77	-0.65	17.89
Switzerland	17.99	0.88	7.22	0.42	55.64
UK	18.98	0.25	5.90	-0.26	66.24
Total	**18.23**	**0.29**	**5.47**	**-0.59**	**34.08**

Table 2.16: CAR for alternative event windows

	(1)		**(2)**	
	CAR	**P-value**	**CAR**	**P-value**
[t-1,t+1] - Investment	0.0048	0.6919	0.0176	0.1523
[t-1,t+1] - Speculative	0.0364	0.0408	0.0436	0.0226
[t-3,t+3] - Investment	0.0011	0.9469	0.0085	0.6437
[t-3,t+3] - Speculative	0.0438	0.211	0.054	0.1754

Note: These CAR are estimated using equation (2.2) with country and year fixed effects. Column (2) does not include UK nor Switzerland.

Table 2.17: Speculative 2^{nd} definition

Variable	(1)	(2)
$\Delta Spread_t$	0.0993***	0.1001***
Investment	0.0051	0.0082
Speculative	0.0223**	0.0260**
Constant	0.0001	0.0002
N	23450	18760
$Adj R^2$	0.0107	0.0111

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Dependent variable is the change in sovereign spreads after the downgrade takes place. *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. For this I use the second definition for *Speculative*, i.e. mean rating of downgraded banks on a given day. All regressions are using country and year fixed effects. Regression (2) does not include UK nor Switzerland.

Table 2.18: Speculative 3^{rd} definition

Variable	(1)	(2)
$\Delta Spread_t$	0.0993***	0.1001***
Investment	0.0038	0.006
Speculative	0.0268**	0.0309**
Constant	0.0001	0.0002
N	23450	18760
$Adj R^2$	0.0107	0.0111

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Dependent variable is the change in sovereign spreads after the downgrade takes place. *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. For this I use the second definition for *Speculative*, i.e. weighted average rating of downgraded. All regressions are using country and year fixed effects. Regression (2) does not include UK nor Switzerland.

Table 2.19: Alternative size threshold - Non linear relationship w/ size - Euro

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.1001***	0.1001***	0.1001***	0.1001***
Downgrade	0.0188**	0.0189**	0.0189**	0.0189**
Down. x Size-10%	0.0074	-	-	-
Down. x Size-25%	-	0.0054	-	-
Down. x Size-50%	-	-	0.0231**	-
Down. x Size-100%	-	-	-	0.0239***
Constant	0.0002	0.0002	0.0002	0.0002
N	18760	18760	18760	18760
$Adj R^2$	0.0111	0.0111	0.0111	0.0111

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regression do not include UK nor Switzerland. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. For downgrades of multiple banks, the average systemic size of all downgraded banks is used. All regressions are using country and year fixed effects.

Table 2.20: Alternative size threshold - Non linear relationship w/ size - Euro - Investment vs Speculative downgrades

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.1001***	0.1001***	0.1001***	0.1001***
Investment	0.0059	0.0059	0.006	0.0059
Speculative	0.0308**	0.0307**	0.0309**	0.0309**
Spec. x Size-10%	0.0215	-	-	-
Inv. x Size-10%	-0.0045	-	-	-
Spec. x Size-25%	-	0.0226	-	-
Inv. x Size-25%	-	-0.0054	-	-
Spec. x Size-50%	-	-	0.0585***	-
Inv. x Size-50%	-	-	0.0057	-
Spec. x Size-100%	-	-	-	0.0581
Inv. x Size-100%	-	-	-	0.0114
Constant	0.0002	0.0002	0.0002	0.0002
N	18760	18760	18760	18760
$Adj R^2$	0.011	0.011	0.011	0.011

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regression do not include UK nor Switzerland. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. For downgrades of multiple banks, the average systemic size of all downgraded banks is used. All regressions are using country and year fixed effects.

Table 2.21: Winsorizing - General analysis

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.2610***	0.2710***	0.2610***	0.2710***
Downgrade	0.0110*	0.0138*	-	-
Investment	-	-	0.0031	0.0049
Speculative	-	-	0.0189*	0.0207*
Constant	0.0001	0.0002	0.0001	0.0002
N	23450	18760	23450	18760
$AdjR^2$	0.0723	0.079	0.0723	0.079

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Even columns include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. Windsorization at 1%, for maximum and minimum values for the change in spreads. All regressions are using country and year fixed effects.

Table 2.22: Winsorizing - Non linear relationship w/ size - Euro - Speculative downgrades

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.2711***	0.2711***	0.2710***	0.2710***
Investment	0.0048	0.0048	0.0049	0.0048
Speculative	0.0206*	0.0205*	0.0207*	0.0207*
Spec. x Size-10%	0.0135	-	-	-
Inv. x Size-10%	-0.0025	-	-	-
Spec. x Size-25%	-	0.0173	-	-
Inv. x Size-25%	-	-0.0045	-	-
Spec. x Size-50%	-	-	0.0466***	-
Inv. x Size-50%	-	-	0.0034	-
Spec. x Size-100%	-	-	-	0.0101
Inv. x Size-100%	-	-	-	0.0088
Constant	0.0002	0.0002	0.0002	0.0002
N	18760	18760	18760	18760
$Adj R^2$	0.0789	0.0789	0.0791	0.0789

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regressions include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. Windsorization at 1%, for maximum and minimum values for the change in spreads. All regressions are using country and year fixed effects.

Table 2.23: Using day fixed effects - General analysis

Variable	**(1)**	**(2)**	**(3)**	**(4)**
$\Delta Spread_t$	0.0919***	0.0901***	0.0919***	0.0901***
Downgrade	0.0223	0.0352	-	-
Investment	-	-	0.0302	0.0549
Speculative	-	-	0.0145*	0.0201**
Constant	0.0017	-0.0022**	0.0017	-0.0022**
N	23450	18760	23450	18760
$Adj R^2$	0.0477	0.0547	0.0477	0.0547

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Even columns include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. All regressions are using country and day fixed effects.

Table 2.24: Using country common factor - General and size analysis

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta Spread_t$	0.0994***	0.0994***	0.0994***	0.0993***	0.0993***	0.0993***
Downgrade	0.0181**	-	0.0179**	0.0180**	0.0181**	0.0180**
Investment	-	0.0073	-	-	-	-
Speculative	-	0.0264**	-	-	-	-
Down. x Size-10%	-	-	0.0094	-	-	-
Down. x Size-25%	-	-	-	0.0108	-	-
Down. x Size-50%	-	-	-	-	0.0269**	-
Down. x Size-100%	-	-	-	-	-	0.0280***
Mkt Index	-0.1592**	-0.1597**	-0.1601**	-0.1603**	-0.1613**	-0.1604**
Constant	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
N	18760	18760	18760	18760	18760	18760
Adj R^2	0.0113	0.0113	0.0113	0.0113	0.0113	0.0113

Legend: * $p < .1$; ** $p < .05$; *** $p < .01$

Note: Regressions include only *Euro* countries. Dependent variable is the change in sovereign spreads after the downgrade takes place. *Downgrade* is a dummy that equals 1 there is a downgrade on the corresponding, and zero otherwise. Similarly *Investment* (*Speculative*) is a dummy that equals 1 if the final rating of the downgraded bank is above (below or equal) D+ and zero otherwise. *Size-X%* is a dummy that equals 1 if the systemic size of the bank (measured by the ratio of its total liabilities to its home country GDP) is above *X%*, or zero otherwise. *Mkt Index* is the daily change in the benchmark market index for the corresponding country. All regressions are using country and year fixed effects.

Chapter 3

Risk-taking and optimal joint liquidity and capital requirements

3.1 Introduction

Before the last financial crisis, regulators had a highly developed system to regulate capital requirements (Repullo, 2004). Nevertheless, there was no formal standard regulating liquidity (Stein, 2013), and the Lender of Last Resort was the main tool to manage banks' liquidity problems (Repullo, 2005). The financial crisis exposed this gap on the regulatory framework, exposing its weaknesses. There has been an important change in the regulatory focus since. Regulation on liquidity standards have become one of the main targets for banks' supervisors (e.g. Basel III).[1]

In general, liquidity and capital have been analyzed in isolation. The former is used to reduce liquidity risk, while the latter to prevent solvency risk. Nevertheless, these tools are not independent (Vives, 2014; Walther, 2015). For instance, requirements on liquid assets will have an effect on

[1] The Basel Committee proposed the *Liquidity Coverage Ratio* (LCR) and the *Net Stable Funding Ratio* (NSFR), while the British FSA released a set of guidances to regulate banks' liquidity (similar to Basel's LCR).

banks' risk choice as well. There is an underlying relationship between capital and liquidity requirements, which will shape the optimal regulation. The aim of this paper is to characterize this relationship between capital and liquidity, i.e. whether these are complements or substitutes.

For this purpose, we construct a theoretical model with a bank that invests in a risky asset, and determines endogenously solvency risk (through monitoring). Additionally, this bank is subject to an exogenous level of early deposit withdrawals, generating liquidity risk. Liquid reserves are used to survive early withdrawals. But liquidity generates a trade-off. On the one hand, increasing liquid assets monotonically reduces liquidity risk. On the other hand, it reduces the share invested in the profitable project. By the same token, this duality of liquidity will affect bank's incentives to monitor. When liquid assets are low, liquidity risk is high and bank's *future expected* value is low, since the likelihood of failing due to deposit withdrawals is high. Hence, monitoring will be low. As we increase liquidity, bank's *future expected* value increases (via a reduction in liquidity risk), and so does the incentives to monitor. But with high monitoring, the opportunity cost of liquidity increases, since each additional unit of liquid funds will imply a reduction in the *future value* of the investment project. Then, further increasing liquidity will decrease bank's incentives to monitor (given the reduction in the investment project).

Using these mechanisms, we analyze the decisions of a regulator that sets both capital and liquidity requirements in order to enhance social welfare. Capital induces monitoring (via *skin in the game*) reducing solvency risk, while liquidity reduces the risk of failing due to deposit withdrawals reducing liquidity risk. Solvency and liquidity risk are independent in the model. Nevertheless, not only we find that the optimal capital and liquidity requirements are interrelated, but they can be complements or substitutes. The degree of complementarity (or substitutability) between these regulatory tools will ultimately depend on the shadow cost of capital.

If capital is inexpensive, the regulator will set a relatively large capital requirement. Then, the bank will have more incentives to monitor (due to the *skin in the game* effect), increasing both bank's *future expected* value as well as the opportunity cost of using liquidity. Further increases on capital will be coupled with reductions on liquidity requirements, since holding liquid assets will be too expensive (in terms of forgone investment). This means that capital and liquidity are substitutes. On the other hand, if capital is expensive, the regulator will set a low capital requirement and bank's monitoring will be relatively lower. Additionally, bank's *future expected* value will be low, just like the *opportunity cost* of liquidity. Then, increasing capital will be accompanied with increases in liquidity requirements, in order to enhance the probability of surviving early withdrawals (given that liquidity is relatively cheap). This means that capital and liquidity requirements are complements.

The model has several important regulatory implications. Regulators trying to enhance financial stability by setting liquidity requirements, might shift bank's incentives towards riskier portfolios. Additionally, a regulator that set independently too stringent capital and liquidity requirements, might reduce social welfare. Then, regulators should recognize the existence of the aforementioned interactions between capital and liquidity requirements, when they maximize social welfare.

The rest of the paper is organized as follows. Section 3.2 reviews some of the previous literature on capital and liquidity. Section 3.3 briefly presents the general setting, bank's maximization problem, and the regulator's optimal capital and liquidity policy. Section 3.4 presents possible extensions for the basic model. Finally, section 3.5 concludes.

3.2 Related literature

Repullo (2004) presents a model where the risk-based capital requirement is a useful way to prevent banks from investing in a gambling asset. Hence, the capital requirement is an efficient tool to reduce solvency risk. On a similar line, Repullo (2005) analyzes the effect of a *Lender of Last Resort* on moral hazard, and finds that it is capital requirement (and not liquidity) what ultimately shapes banks' risk profile. Then, the existence of a *Lender of Last Resort* will have no impact on banks' risk-taking. Similarly, Freixas et al. (2011) find that a central bank might improve liquidity redistribution by using interest rates. Particularly, in an environment with high uncertainty (e.g. crisis period), a reduction on interest rates will improve the reallocation of liquidity between banks, enhancing financial stability. On a different paper, Calomiris et al. (2015) analyze the use of liquidity requirements, and find that cash reserves (together with deposit insurance) are useful to induce a proper risk management. In this setting liquidity acts as a self-commitment device to monitor investments. Our study contributes to these papers, by focusing on the joint use of liquidity and capital requirements, and their effect on banks' behavior.

On a related paper, De Nicoló et al. (2014) analyze the use of capital and liquidity using a dynamic model. They argue that these regulatory tools are substitutes: while capital has a hump-shaped relationship with social welfare, liquidity unambiguously reduces lending and welfare. On a recent contribution, Vives (2014) uses the idea of strategic complementarity (between investors' decisions) to analyze capital and liquidity requirements. In this environment, these are substitutes, at least partially, since they are used to solve different problems (solvency and liquidity). Additionally, the author finds that liquidity requirements become more important if there is more disclosure on banks' assets. Finally, Walther (2015) analyze the effects of macro-prudential (e.g. liquidity) and micro-prudential regulation (e.g. capital). The author finds that using only one of these tools would exacerbate the severity of the optimal measure, arguing that capital and liquidity are imperfect substitutes. Our model complements this stream of literature by analyzing a different mechanism in which liquidity affects banks' decisions: it reduces liquidity risk, but decreases the share of long term investments. Using this approach, we allow for a complementarity effect between capital and liquidity requirements (as opposed to previous literature). The final direction of this relationship between the regulatory tools, will depend on the shadow cost of capital.

3.3 The model: General setting

We model a three-periods economy, $t \in \{0, 1, 2\}$, where all agents are risk neutral and there is a zero discount factor. In this economy, there is a unique bank that can invest in a profitable project (loan) or a liquid asset. To do this, the bank uses three different sources of funds: deposits, other debt (e.g. bonds) and capital.

The investment opportunity is a long term project that requires one unit of funds at $t = 0$, and returns $M > 1$ at $t = 2$ when it is successful. Bank's monitoring effort $\theta \in [0, 1]$ will determine the success probability of the project. Then, $(1 - \theta)$ represents bank's *solvency risk*. Nevertheless, monitoring effort is costly for the bank. Following DellAriccia and Marquez (2006) and Allen et al. (2011b), we model this cost as a quadratic function $\frac{c}{2}\theta^2$.

Demand deposits (d) are one of the sources of funds for the bank. These are assumed to be limited to a fixed amount. Deposits can be withdrawn at any moment, and are completely insured by a deposit insurance scheme, allowing us to normalize interest rates to one.[2] Then, depositors have no incentives to monitor the bank at any stage in the model, nor to withdraw early (unless they have liquidity needs).

Similar to Diamond and Dybvig (1983), some depositors will have liquidity needs at an intermediate period $t = 1$. But in this model, the amount $\beta \in [0, d]$ of early withdrawals is unknown beforehand. Nevertheless, it follows a known distribution function with cdf $F(\beta)$. We do not restrict this probability to a particular function, but only assume that it is log-concave, continuous and differentiable. If the bank is unable to satisfy depositors' withdrawals, it is liquidated at period $t = 0$.[3]

In order to prevent bankruptcy due to early withdrawals, the bank constitutes liquidity reserves. But this has a downside, since it reduces the resources available to investment in the long term project. The bank allocates a magnitude λ to cash reserves, while the remaining $1 - \lambda$ is invested in the long term project. Whenever liquidity reserves are less than deposit withdrawals ($\beta > d$), the bank is liquidated at $t = 1$ and makes zero profit. Hence, $F(\lambda)$ represents the likelihood of surviving deposit withdrawals at $t = 0$ (*survival probability*), and $1 - F(\lambda)$ is the *liquidity risk*.

Since the bank needs to invest one unit of funds and uses d deposits, the remaining $1 - d$ can be financed using capital k or bonds b. Using capital

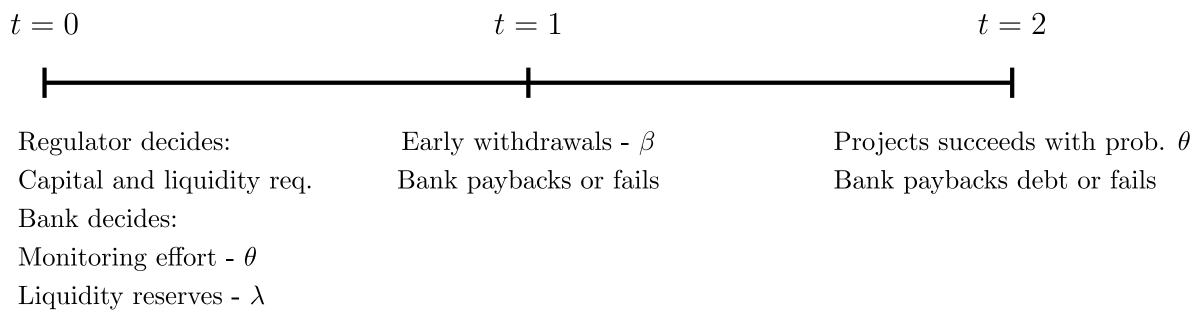
[2] Assuming that banks pay a flat payment for this insurance does not alter out main results.

[3] We assume that the liquidation value of the long term investment is null. In the appendix we relax this assumption.

conveys a substantial cost $\rho > 1$. In the general framework, we assume that bonds are insured, which allows to normalize its cost to one as well.

In the context of this model, we analyze the decision made by the bank in terms of monitoring effort and liquidity reserves. Additionally, we assess the optimal requirements for capital and liquidity, that a regulator would choose.

Time line of the model



3.3.1 Banks' maximization problem

Before analyzing the regulator's optimal policy, we need to determine bank's maximizing strategy, since this will be an important factor driving the choice of the regulator.

First, we analyze bank's optimal monitoring effort and liquidity reserves. Then, we will assess the effect of liquid assets on banks' monitoring θ. Liquidity has a dual effect on bank's monitoring decision. On the one hand, it reduces the likelihood of failing due to early withdrawals. On the other hand it decreases the share of funds invested in the long term asset, decreasing bank's future value if the project is successful.

In this section, we consider that other debt b is insured as well. This means that $1-k$ is the amount of secured debt (deposits d and other debt b) held by the bank. These deposits and debt are paid only if the bank survives early withdrawals and the project succeeds (there is limited liability).

Then, banks decide on their asset structure (liquidity or long term investment) and their monitoring effort, in order to maximize the following problem: [4]

$$\Pi \equiv \max_{\substack{0\leq\lambda\leq d \\ 0\leq\theta\leq 1 \\ 0\leq k\leq 1-d}} \int_0^\lambda \theta\left[M(1-\lambda)+(\lambda-\beta)-(d-\beta)-(1-k-d)\right]f(\beta)d\beta-\frac{c}{2}\theta^2-\rho k, \tag{3.1}$$

where $M(1-\lambda)$ stands for the profits derived from the long term investment, and $(\lambda-\beta)$ is the cash remaining after paying back early deposit withdrawals. Finally, the bank has to pay $(d-\beta)$ and $(1-k-d)$ at period two, which represent all remaining depositors and other debt. These payments are conditional on the bank surviving early deposit withdrawals, i.e. $\beta\in[0,\lambda]$, and the long term project being successful (with probability θ).

Using the *Leibniz's rule* for differentiating under the integral, we can get the First Order Conditions (*FOC*s) for the optimal monitoring and liquidity:

$$[\theta]:\ \theta_b=\frac{1}{c}\int_0^\lambda\left[M(1-\lambda)-(1-k-\lambda)\right]f(\beta)d\beta=\frac{F(\lambda)}{c}\left[M(1-\lambda)+\lambda-(1-k)\right], \tag{3.2}$$

$$\begin{aligned}[\lambda]:\ &\theta\left[M(1-\lambda)+\lambda-(1-k)\right]f(\lambda)-\int_0^\lambda\theta(M-1)f(\beta)d\beta=0\\ &\Leftrightarrow F(\lambda)\,\theta(1-M)+\theta\left[M(1-\lambda)+\lambda-(1-k)\right]f(\lambda)=0.\end{aligned} \tag{3.3}$$

[4]In the absence of regulation on capital, banks would always choose $k=0$, since the cost of capital is greater than the cost of secured debt $\rho>1$ (Repullo, 2005)

Equation (3.2) shows that bank's monitoring effort increases with the probability of surviving liquidity withdrawals, and bank's future cash flows (that depends on the amount invested in the investment project). In these cases, the bank will be willing to monitor more diligently in order to boost the likelihood of success and receive this higher payment. Additionally, it is straightforward from equation (3.2) that increasing capital k will lead to a higher θ_b ($\frac{\partial \theta_b}{\partial k} > 0$). This is explained by the fact that the bank has more *skin in the game* when it pledges more capital.

As argued before, the relationship between θ and λ is an important factor. Monitoring effort increases with bank's revenues, while liquidity reserves have a dual effect on these *expected* profits. This duality will shape the relationship between liquidity and monitoring effort. For relatively low levels of liquidity, increasing liquid assets will boost bank's *future expected* profits by increasing the *survival probability.* Nevertheless, when liquidity reserves are high, the effect on the survival probability will be dominated by the reduction on the share invested on the long term project. Then, bank's *future expected* profits will decrease, reducing the incentives to monitor the investment. Both effects coupled together will determine the relationship between θ and λ, as stated in the following proposition:

Proposition 1 *The optimal monitoring effort chosen by the bank is a hump-shaped function of liquidity reserves.*

Proof. *See proof in the appendix 3.5* ■

Proposition 1 entails that liquidity has an important effect on solvency risk. This link between liquidity and monitoring, will be the main driver of the interaction between capital and liquidity requirements from a regulatory perspective.

Finally, equation 3.3 implies that the bank will choose the level of liquidity that maximizes its profits. But, if bank's profits are higher, the incentives to monitor will increase as well. Then, if liquidity maximizes the *future expected* value of the bank, it will maximize the monitoring effort as well.

Lemma 1 *The level of liquidity chosen by the bank, will maximize the monitoring effort.*

Proof. *See proof in the appendix 3.5* ■

3.3.2 Regulator's maximization problem

Now, we analyze the problem of a regulator that sets capital and liquidity requirements to improve social welfare. But in order to induce the proper effect, the regulator takes into consideration bank's optimal monitoring response to the regulatory environment. That is, how would the bank react to capital and liquidity regulation.

Capital requirements are used to increase bank's *skin in the game*, improving their incentives to monitoring. On the other hand, liquidity requirements are used to reduce the likelihood that banks fail due to excessive early withdrawals. The objectives of these regulatory tools are different, since solvency and liquidity risk are independent in the model. Nevertheless, there is an interdependence between the optimal capital and liquidity requirements, which arises from the effect of liquidity on monitoring (proposition 1). This interaction will shape the regulatory policy, providing a taxonomy for the optimal capital requirement in terms of liquidity (or the optimal liquidity requirement in terms of capital).

In this context, the regulator solves the following problem, taking as given bank's optimal monitoring response from equation (3.2):

$$\Pi_R \equiv \max_{\substack{0\leq k\leq 1-d\\ 0\leq\lambda\leq d}} \int_0^{\lambda} \theta_b M(1-\lambda) f(\beta) d\beta + \lambda - (1-k) - \frac{c}{2}\theta_b^2 - \rho k.$$

Given that the regulator is not protected by limited liability, it always considers total debt $(1-k)$ in its utility function. We can restate the above problem as follows:

$$\Pi_R \equiv \theta_b \chi(\lambda) - (1-\lambda) - \frac{c}{2}\theta_b^2 - (\rho-1)k, \tag{3.4}$$

where $\chi(\lambda) = F(\lambda)M(1-\lambda)$ represents the expected value for the loan (conditional on the project being successful). Additionally, $(1-\lambda)$ represents the cost to invest in the risky project, while $(\rho - 1)$ stands for the "*shadow cost*" of using capital (since it is more expensive compared to deposits or insured debt). The corresponding *FOC*s for capital and liquidity are:

$$[k] : \frac{\partial\theta_b}{\partial k}[\chi(\lambda) - c\theta_b] = \rho - 1, \tag{3.5}$$

$$[\lambda] : 1 + \theta_b \frac{\partial\chi(\lambda)}{\partial\lambda} + \frac{\partial\theta_b}{\partial\lambda}[\chi(\lambda) - c\theta_b] = 0. \tag{3.6}$$

The term in brackets on the Left Hand Side (LHS) of equation (3.5) presents the marginal benefit from monitoring. From equation (3.2), we know that capital increases bank's monitoring. Then, the whole term presents the change in the expected benefits associated with changes in capital. The corresponding Right Hand Side (RHS) presents the *shadow cost* of capital.

It is noteworthy the fact that regulator's liquidity (equation 3.6) is always higher than bank's liquidity choice (equation 3.3). This means that, the liquidity requirements set by the regulator are binding for the bank. The reason is that liquidity has a higher social than private value: it reduces the losses when the bank is liquidated due to early withdrawals. This social benefit is not considered by the bank since it is protected by limited liability, but the regulator takes into account this on its maximization problem. The following lemma formally express this result:

Lemma 2 *The optimal liquidity requirement for the regulator is always binding for the bank.*

Proof. *See proof in the appendix 3.5* ■

In order to characterize the relationship between capital and liquidity requirements, first we need to analyze the effect of the latter on social welfare. There are three channels in which liquidity affects the utility function of the regulator. These can be analyzed in equation (3.6). The first term (1) shows that higher liquidity always decreases the social cost of bank's failure.[5] The second term shows the effect of liquidity in the expected value for the investment project ($\frac{\partial \chi(\lambda)}{\partial \lambda}$). Here, λ increases the survival probability at the cost of reducing the long term investment. This *trade-off* leads to a hump-shaped relationship between liquidity and the expected value for the long term investment. Finally, the last term shows that liquidity reduces bank's incentives to monitor ($\frac{\partial \theta_b}{\partial \lambda}$), given the marginal benefit from monitoring ($\chi(\lambda) - c\theta_b$). Since the liquidity requirement is binding for the bank (lemma 2), and bank's liquidity choice maximizes the its monitoring effort (lemma 1), increasing liquidity requirements will reduce bank's monitoring.

[5]The recovery value of liquidity is always higher than the liquidation value of the long term project. The model assumes that the recovery value for the long term asset is zero.

Then, this last term represents the reduction in the expected payment from monitoring, due to an increase in liquidity.

As stated before, liquidity is used to enhance the likelihood of surviving early withdrawals, while capital is used to reduce solvency risk. Despite the fact that liquidity and solvency risk are independent, liquidity and capital requirements are interrelated. Hence, we analyze the effect of capital on the optimal liquidity requirement.

Let us start assuming that k is low, and bank's incentives to monitor are low (just like the *future expected* value of the project). As we increase capital, bank's incentives to monitor raise (through the *skin in the game* channel), boosting the *future expected* value of the project. Then, in order to capitalize the larger *future expected* value of the project, regulator's incentives to increase liquidity requirements will be higher (the regulator increases the probability of survival by increasing liquidity). On the other hand, if k is too large (and so is bank's monitoring), the *opportunity cost* of liquidity is higher, since the *future expected* payment from the long term project is high. Then, further increases in capital will be accompanied by reductions in liquidity requirements. This idea is formally presented in the following lemma:

Lemma 3 *The optimal liquidity requirements λ_R^* are a hump-shaped response to capital levels.*

Proof. *See proof in the appendix 3.5* ■

In order to complement our previous intuition, let us analyze the changes in equation (3.6) whenever there is a change in capital, and evaluate it on the optimal liquidity requirement ($\lambda_R^*(k)$):

$$\frac{\partial^2 \Pi_R(k, \lambda_R^*(k))}{\partial \lambda \partial k} = \frac{\partial \theta_b}{\partial k}\frac{\partial \chi(\lambda)}{\partial \lambda} + \frac{\partial^2 \theta_b}{\partial \lambda \partial k}[\chi(\lambda) - c\theta_b] - c\frac{\partial \theta_b}{\partial \lambda}\frac{\partial \theta_b}{\partial k} \tag{3.7}$$

The first term shows the effect of changes in capital on monitoring, given the effect of liquidity on the expected value of the project. Then, it represents the effect of capital in the opportunity cost of liquidity. Increasing capital leads to a higher monitoring, which in terms increases expected value of the investment project, as well as the opportunity cost of the liquidity. This creates a substitution effect between λ and k. The second term shows that higher capital will reduce the contraction in monitoring effort that is associated with higher liquidity requirements, since $\frac{\partial^2 \theta_b}{\partial \lambda \partial k} = \frac{f(\lambda)}{c} > 0$. This suggests a complementarity effect between λ and k. Finally, the last term shows the reduction in the monitoring cost induced by the changes in capital and liquidity. This reinforces the complementarity effect between these tools. Then, lemma 3 implies that when k is low, capital and the optimal liquidity requirements are complementary. On the other hand, when k is higher, capital and the optimal liquidity requirement are substitutes.

Finally, we analyze the effect of changes in liquidity on the optimal capital requirement. Let us assume a situation with low liquidity with a low likelihood of surviving early withdrawals. Hence, the incentives of the regulator to use capital are low as well (even with perfect monitoring, the expected value of the project is low due to liquidity risk). As we increase liquidity, survival probability increases as well, driving up regulator's incentives to use capital to induce monitoring. On the other hand, if liquidity is higher (as well as survival probability), the share of funds invested in the long term asset is low. Then, regulator's incentives to use capital to induce monitoring is lower, since the *future expected* value of the project is low (due to a low investment). This idea can be formally stated as the following lemma:

Lemma 4 *The optimal capital requirements k_R^* are a hump-shaped response* *to liquidity levels.*

Proof. *See proof in the appendix 3.5* ■

To provide additional insights on this, let us rewrite equation (3.7), but evaluating it on the optimal capital requirement as a function of liquidity ($k^*_R(\lambda)$):

$$\frac{\partial^2 \Pi_R(k^*_R(\lambda), \lambda)}{\partial k \partial \lambda} = \frac{\partial \theta_b}{\partial k}\left[\frac{\partial \chi(\lambda)}{\partial \lambda} - c\frac{\partial \theta_b}{\partial \lambda}\right] + \frac{\partial^2 \theta_b}{\partial k \partial \lambda}[\chi(\lambda) - c\theta_b]. \tag{3.8}$$

The first term reflects the product between the change in monitoring due to changes in capital, and the variation of the marginal benefit from monitoring associated with a change in liquidity. This term inside brackets shows the effect of increasing liquidity on the marginal value of monitoring. To understand better the behavior of this term, let us define λ_a such that for lower values, the term inside brackets is positive, i.e. $[\chi'(\lambda) - c\frac{\partial \theta_b}{\partial \lambda}] > 0$.[6] Then, increasing liquidity will increase the marginal utility of monitoring when $\lambda < \lambda_a$ (complementarity effect), while for $\lambda > \lambda_a$ increasing liquidity will reduce the marginal benefit of monitoring (substitutability effect). The second term of equation (3.8) reflects a complementarity effect between λ and k. The first factor ($\frac{\partial^2 \theta_b}{\partial k \partial \lambda}$) shows that liquidity increases the sensitivity of the monitoring effort to changes in capital (given a reduction in the liquidity risk).[7] The second factor is the marginal benefit from monitoring, which is positive. Then, lemma 4 implies that for high levels of λ, liquidity and capital are substitutes. On the other hand, if λ is low, liquidity and capital

[6] The existence of λ_a is guaranteed, since $f(\lambda)$ is log-concave and $k^*_R(\lambda)$ is an increasing function on $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} > 0$.

[7] Remember that $\frac{\partial^2 \theta_b}{\partial \lambda \partial k} = \frac{f(\lambda^*_R)}{c} > 0$.

are complementary.

So far, the analysis shows that capital and liquidity requirements can be complements or substitutes, depending on their quantities. For low levels of liquidity (capital), these tools are complements, but for higher levels of liquidity (capital) they become substitutes. In equilibrium, when the regulator chooses capital and liquidity requirements simultaneously, the degree of complementarity (or substitutability) depends on the *shadow cost* of capital.

Whenever capital is relatively cheap (below $\hat{\rho}$), the regulator will find it optimal to use relatively large amounts of capital. This means that bank's incentives to monitor the investment project are higher, increasing the *opportunity cost* of liquidity. Hence, further increases in capital should be accompanied by reductions in liquidity, since these liquid assets will become even costlier (lemma 4). Then, k and λ are substitutes. On the other hand, when the cost of capital is higher (above $\hat{\rho}$), regulators will set lower requirements (since it is costlier than before). The bank will have little incentives to monitor the investment, and the *opportunity cost* of liquidity will be lower. Then, further increasing capital should be accompanied by increases in liquidity, which is a relatively inexpensive tool to enhance survival probability. Hence, k and λ are complementary tools. This idea can be summarized in the following proposition:

Proposition 2 *There is a level $\hat{\rho}$ for the cost of capital, such that: for $\rho < \hat{\rho}$ liquidity and capital are substitutes, but for $\rho > \hat{\rho}$ they become complementaries.*

Proof. *See proof in the appendix 3.5* ■

This proposition implies that the shadow cost of capital will determine whether liquidity and capital are complementary or substitutes tools.

In order to further explain this proposition we use Figure 3.1. Here, $k_R^*(\lambda)$ represents regulator's optimal capital response to a given level of liquidity, and $\lambda_R^*(k)$ stands for the regulator's optimal liquidity response to a given level of capital. The intersection between these functions will determine the optimal regulatory policy in terms of capital and liquidity requirements. Additionally, the line $\bar{\Pi}_{12}(\lambda, k)$, shows all the possible combinations between k and λ such that the second-order mixed derivative equals zero, i.e. $(\frac{\partial^2 \Pi_R}{\partial\lambda\partial k} = 0)$. This means that, the maximum values for $\lambda_R^*(k)$ and $k_R^*(\lambda)$ lie in the line $\bar{\Pi}_{12}$. From this figure, we observe that to the left of the intersection between $k_R^*(\lambda)$ and $\bar{\Pi}_{12}$, liquidity and capital are complementaries (if the regulator choses k, with an exogenous λ). On the other hand, to the right of the intersection between these two curves, k and λ are substitutes.[8]

From the regulator's FOCs (equations 3.5 and 3.6), we know that the cost of capital only affects the optimal capital requirement $k_R^*(\lambda)$, but does not affect the optimal liquidity requirement $\lambda_R^*(k)$. Then, a reduction on ρ will lead to a parallel upward shift on $k_R^*(\lambda)$, but will have no effect on $\lambda_R^*(k)$.

For example, let us assume a sufficiently high cost of capital ρ_0. Since capital is socially costly, the regulator will choose a low level of capital requirements, given by $k_R^*(\lambda; \rho_0)$. Additionally, regulator's choice of liquidity $\lambda_R^*(k_{\rho_0}^*)$ will be low as well. Then, both instruments will be complementary tools. As the cost of capital decreases, regulator's incentives to use k will increase (we move along the line $\lambda_R^*(k)$ to the new intersection). This reduction on the shadow cost of capital, leads to a higher use of liquidity as well (but at a decreasing rate). Consider now the situation when the cost of capital is sufficiently low (ρ_1). The new equilibrium lies to the right of the $\bar{\Pi}_{12}$ line, on the decreasing section of $\lambda_R^*(k)$. In this region, the reduction in the expected

[8]A similar analysis arises when analyzing the intersections between $\bar{\Pi}_{12}$ y $\lambda_R^*(k)$.

value of monitoring, is exceeded by the increase in the opportunity cost of liquidity (when capital increases). Then, the optimal liquidity choice for the regulator will be lower (the tools become substitutes).

3.4 Extensions

In this section we present a set of extensions on the basic setup. We start introducing a modified version of the model, which includes a Lender of Last Resort (LoLR). This will have as a consequence the disappearance of liquidity risk of the model, i.e. the bank will no longer fail due to early withdrawals, since it can always come the LoLR to obtain additional liquidity. Then, we present a model that includes the possibility of fire sales, i.e. the bank is able to sell long term assets at an intermediate period in order to obtain additional liquid funds. This will reduce liquidity risk, but it will not eliminate it though. Afterwards, we extend the model by assuming that uncorrelated loans' success probability. In this context we also introduce a systemic shock, which is independent of the monitoring effort. This will introduce a new effect of capital, i.e. it will work as a buffer enhancing bank's ability to survive systemic shocks. Then, we include an extension with a wholesales market. In this case, the bank will obtain a fraction of its funds from short term sophisticated creditors. In this setting, the bank will have to rollover part of this uninsured debt. In order to do this, it will have to pay creditors an interest rate that compensates for the level of solvency risk. Finally, we include an extension introducing the interbank market.

3.4.1 Lender of Last Resort

We can extend the model by including a LoLR. In this case, if deposit withdrawals exceed liquidity reserves, the bank can obtain the additional liquid funds via a LoLR.[9] But in order to receive these funds, the bank will pay the social cost of liquidity (exogenous ρ_L). [10]

If the LoLR always provides liquidity support at $t = 1$, liquidity risk disappears, i.e. the bank is always able to satisfy deposit withdrawals. The reason to hold liquidity (for the bank) will change. Then, the bank will have incentives to raise liquid funds only to reduce the likelihood of requiring financial assistance from the LoLR. The bank will solve the following problem:

$$\Pi \equiv \int_0^{\lambda} \theta \left[M(1-\lambda) - (1-k-\lambda) \right] f(\beta) d\beta +$$
$$\int_{\lambda}^{d} \theta \left[M(1-\lambda) - (1-k-\lambda) - (\rho_L - 1)(\beta - \lambda) \right] f(\beta) d\beta - \frac{c}{2}\theta^2 - \rho k.$$

The first integral represents the case when liquidity reserves are enough to satisfy early withdrawals (similar to the original setting). The second integral corresponds to the case when liquidity is not enough, and the bank needs to get liquidity from the LoLR. Note that in this case, the amount of deposits due at $t = 2$ is lower $(1 - k - \beta)$, since $\beta > \lambda$. Nevertheless, the bank has to pay ρ_L for each unit of liquidity that requires from the LoLR. The corresponding FOCs with respect to monitoring and liquidity are:

---

[9] For the sake of simplicity, the LoLR will be the same agent who imposes capital and liquidity requirements, i.e. the regulator.

[10] This cost of liquidity will have an upper and lower bound in order to have an interior solution, i.e. $M < \rho_L < \frac{M}{d}$. If liquidity is too inexpensive, the bank (and regulator) will find it optimal to set $\lambda = 0$ and rely always on the LoLR. On the other hand, if liquidity is too expensive the bank will not use the LoLR facility, since its cost would be prohibitive.

$$[\theta]:\ \theta_L^* = \frac{M(1-\lambda)-(1-k-\lambda)-\int_\lambda^d(\rho_L-1)(\beta-\lambda)f(\beta)d\beta}{c}$$

$$[\lambda]:\ 1-M+(1-F(\lambda))(\rho_L-1)=0$$

Since there is no liquidity risk on the project, its future expected value is higher. This increases bank's incentives to monitor. By the same token, liquidity reserves are going to be lower compared to the baseline model. The relationship between monitoring and liquidity is still hump-shaped. But the mechanism is slightly different: liquidity reduces the amount invested in the long term asset, but it reduces the need to rely on the LoLR. This last effect is particularly strong when the cost of liquidity is sufficiently large.

Proposition 3 *When the bank is able to receive liquidity support from a LoLR, monitoring effort is a hump-shaped function of liquidity, and the optimal level of liquidity will be such that maximizes monitoring (similar to the baseline model). Nevertheless, the mechanism is different: increasing liquidity reduces the proportion invested in the long term project (like in the basic setup), but instead of reducing liquidity risk it will reduce the likelihood of using the "expensive" LoLR facility. Finally, it is worth mentioning that a bank protected by a LoLR will choose a higher monitoring effort, since there no liquidity risk affecting the long term project.*

Proof. *See proof in the appendix 3.5* ■

In a setting with a LoLR, the regulator solves the following problem:

$$\Pi_R \equiv \int_0^{\lambda} \theta \left[M(1-\lambda)\right] f(\beta)d\beta + \int_{\lambda}^{d} \left[\theta M(1-\lambda) - \rho_L(\beta-\lambda)\right] f(\beta)d\beta - (1-\lambda-k) - \frac{c}{2}\theta^2 - \rho k.$$

Note that a regulator acting as a LoLR will pay the cost of liquidity every time the bank does not have enough liquid assets to pay for deposit withdrawals (regardless of whether the project is successful and the bank pays for this facility, or not). The corresponding FOC's for capital and liquidity are:

$$[k]:\; k_R^* = 1-\lambda-c(\rho-1)+\rho_L\int_{\lambda}^{d}(\beta-\lambda)f(\beta)d\beta$$

$$[\lambda]:\; \frac{\partial\theta}{\partial\lambda}\left[1-\lambda-k+\rho_L\int_{\lambda}^{d}(\beta-\lambda)f(\beta)d\beta\right] - M\theta + 1 + \rho_L\int_{\lambda}^{d}(\beta-\lambda)f(\beta)d\beta = 0$$

In this case, the regulator will set higher capital requirements, compared to the case with no LoLR. The reason is that higher capital will induce monitoring, which in turn increases the probability that the regulator receives the payment from the bank corresponding to the LoLR loan. Additionally, we know that increasing liquidity will reduce the optimal capital requirement $\frac{\partial k_R^*}{\partial\lambda} < 0$, i.e. capital and liquidity are substitutes.

Proposition 4 *When the regulator acts as a LoLR, the optimal capital requirement is a decreasing function liquidity. This means that liquidity and capital are substitutes in this setting.*

Proof. *See proof in the appendix 3.5* ■

3.4.2 Fire Sales

Previously, we assume that the liquidation value for the long term project was zero. If liquidity reserves are not enough to pay for deposit withdrawals, liquidating the long term asset would not help closing this gap. Now relax this assumption, and allow the bank to liquidate part of its long term investment to meet any remaining liquidity demand that can not be satisfied using only liquid reserves. Nevertheless, this liquidation comes at a cost, since in order to obtain one additional unit of liquidity we need to liquidate $L > 1$ of long term assets (loans) at $t = 1$. That is, the investment project is sold at a fire sale price.

In this setting, the bank solves the following problem:

$$\begin{aligned}\Pi \equiv & \int_0^{\lambda} \theta \left[M(1-\lambda) - (1-k-\lambda)\right] f(\beta) d\beta + \\ & \int_{\lambda}^{\overline{\beta}} \theta \left\{M\left[1-\lambda-(\beta-\lambda)L\right] - (1-k-\beta)\right\} f(\beta) d\beta - \frac{c}{2}\theta^2 - \rho k.\end{aligned}$$

The first integral correspond to the case in which liquidity is sufficient to pay early withdrawals. The second integral shows the case when liquidity is not enough, and the bank needs to liquidate part of the long term asset. Note that the upper bound for this integral is $\overline{\beta}$. For deposit withdrawals beyond this level, the bank can not raise enough liquidity to satisfy withdrawals, even in the case that all the long term project is liquidated. It is noteworthy the fact that, if the bank survives early withdrawals by liquidating assets, the amount invested in the project is lower. Additionally, the proportion of deposits due at $t = 2$ is lower, since $\beta > \lambda$. The corresponding FOCs for monitoring and liquidity are:

$$
\begin{aligned}
[\theta]:\ \theta^* = & \frac{1}{c}F(\lambda)\left[M(1-\lambda)-(1-k-\lambda)\right]+ \\
& \frac{1}{c}\int_{\lambda}^{\overline{\beta}}\left\{M\left[1-\lambda-(\beta-\lambda)L\right]-(1-k-\beta)\right\}f(\beta)d\beta
\end{aligned}
$$

$$
[\lambda]:\ F(\lambda)(1-M)+\left[F(\overline{\beta})-F(\lambda)\right]M(L-1)=0
$$

In this case, monitoring will be higher. The reason is that liquidity risk is lower, given the option to liquidate long term project in an intermediate period. Hence, for each level of liquidity monitoring will be higher compared to the case with no fire sales. By the same token, liquidity reserves will be lower, since the bank is less subject to liquidity risk.

Lemma 5 *When the bank is able to liquidate investment, its optimal liquidity choice increases with the liquidation cost of the long term asset.*

Proof. *See proof in the appendix 3.5* ■

In this case, the regulator sets capital and liquidity requirements to solve the following problem:

$$
\Pi_R \equiv \int_0^{\lambda}\theta M(1-\lambda)f(\beta)d\beta+\int_{\lambda}^{\overline{\beta}}\theta M\left[1-\lambda-(\beta-\lambda)L\right]f(\beta)d\beta-(1-k-\lambda)-\frac{c}{2}\theta^2-\rho k.
$$

Note that in this problem, the probability of failing due to early withdrawals is lower. Nevertheless, regardless of whether the project succeeds or fails, the regulator will always take into account total debt $(1-k-\lambda)$. The corresponding FOCs for capital and liquidity are:

$$[k]: \; \frac{\partial \theta_b}{\partial k} F(\lambda) M(1-\lambda) + \frac{\partial \theta_b}{\partial k} \int_{\lambda}^{\overline{\beta}} M \left[1 - \lambda - (\beta - \lambda) L\right] f(\beta) d\beta - c\theta_b \frac{\partial \theta_b}{\partial k} = \rho - 1$$

$$[\lambda]: \; 1 - F(\lambda)\theta_b M + \int_{\lambda}^{\overline{\beta}} \theta_b M(L-1) f(\beta) d\beta - \theta_b M(1-\lambda) = 0$$

3.4.3 Uncorrelated loans

So far, we implicitly assume that all long term assets were perfectly correlated, i.e. θ determines the success probability for all investment projects. This means that either all loans pay or none of them do so. We relax this by assuming that all projects are completely independent, i.e. some of the loans will succeed while some other will fail. Then, if we have a continuum of projects, θ will determine the proportion of successful ones.

In order to introduce some uncertainty on bank's decision, we include a systemic shock $\gamma \in [0, 2]$ that affects the return of bank's investment project. This shock takes place at period $t = 2$, affecting the return of the long term project, , such that $E(\gamma \times M) = M$. [11] The realization of this shock is independent of the monitoring effort (and credit risk).

This shock is unknown beforehand, but it follows a known distribution with cdf $G(\gamma)$. Similar to liquidity withdrawals, we only assume that the corresponding probability density function $g(\gamma)$ is log-concave and smooth.

Whenever $\gamma = 1$, the investment project's return are unaffected, i.e. the long term asset yields M when successful. As we decrease γ, the payment

[11] Loans' expected value is the same as in the baseline model.

of the project decreases. In the extreme case when $\gamma = 0$, the project is completely worthless, despite what the monitoring effort is. On the other hand, if $\gamma = 2$ the investment is twice as profitable compared to the baseline scenario. We may interpret this, as the realization of the state of nature that affects evenly all investment projects in the economy, e.g. for high γ investment's yields are high across the economy, while for a lower γ the yields for any investment project is low. Then, if the state of nature γ is sufficiently low (i.e. below $\underline{\gamma}$), the return of those successful projects might not be sufficient to pay bank's creditors, i.e. the bank becomes insolvent and fails (we assume a null recovery value in this case). The tolerance to this systemic shock will depend on bank's balance sheet structure.

In this setting, capital will have a dual effect on monitoring. First, the bank will increase θ via the usual *skin on the game* channel. Additionally, by reducing the proportion of assets funded with deposits (lowering bank's limited liability), capital will create a buffer against unexpected systemic shocks. This buffer will allow the bank to survive shocks that otherwise would have led to failure. This will further raise bank's incentives to monitor.

Then, the bank solves the following problem:

$$\Pi \equiv \int_0^\lambda \left\{ \int_{\underline{\gamma}}^2 \theta \left[\gamma M(1-\lambda) - (1-k-\lambda) \right] g(\gamma) d\gamma \right\} f(\beta) d\beta - \frac{c}{2}\theta^2 - \rho k.$$

If $\underline{\gamma} < \gamma$ the bank will fail, irrespective of the monitoring effort, since the yield from the long term project ($M \times \gamma$) would not be enough to pay back debt. Then, the threshold for the systemic shock such that the bank fails is given by $\underline{\gamma} = \frac{1-\lambda-k}{M(1-\lambda)}$. Note that $\underline{\gamma}$ decreases with k and λ. This means that capital and liquidity increase the tolerance to a systemic shock, allowing the bank to survive a deeper shock. The corresponding FOCs are:

$$[\theta]: \ \ \theta_{SR} = \frac{F(\lambda)\left\{\int_{\underline{\gamma}}^{2}\left[\gamma M(1-\lambda)-(1-k-\lambda)\right]g(\gamma)d\gamma\right\}}{c}$$

$$[\lambda]: \ \ \int_{\underline{\gamma}}^{2}\left\{f(\lambda)\left[\gamma M(1-\lambda)-(1-k-\lambda)\right]+F(\lambda)(1-M\gamma)\right\}g(\gamma)d\gamma$$

Similar to the baseline model, θ_{SR} will be a hump-shaped function of λ in the presence of a systemic shock. For low levels of liquidity, increasing liquid assets enhance bank's incentives to monitor the project. On the other hand, when liquidity reserves are higher, further increases in liquid assets will result in lower monitoring.

Proposition 5 *When bank's loans are uncorrelated and there is a systemic shock, monitoring continues to be a hump-shaped function of* λ*, and bank's liquidity choice will maximize* θ_{SR}*.*

Proof. *See proof in the appendix 3.5* ■

3.4.4 Wholesales Market

Now we introduce an alternative source of funding. The bank uses deposits d, capital k and short term uninsured debt $(1-d-k)$, e.g. wholesales market. This debt is ought to be paid at period $t=1$, but creditors might be willing to rollover debt until period $t=2$ (for the corresponding price). But in order to do so, they demand a higher payment, which depends on bank's solvency risk. We assume these creditors are sophisticated, i.e. they are able to perfectly observe bank's monitoring effort θ at $t = 1$. Hence, they will charge $\frac{1}{\theta}$ for each unit they rollover. [12]

In this setting, whenever deposit withdrawals are higher than bank's liquidity reserves ($\beta > \lambda$), the bank is liquidated and makes zero profit. But when liquidity is sufficient to satisfy early deposit withdrawals we may face two different cases. If deposit withdrawals are sufficiently small, the bank does not need to rollover short term debt, i.e. cash reserves (after paying depositors) are enough to pay short term creditors at $t = 1$. This occurs for $\beta < \lambda - (1 - d - k)$. The alternative is a situation in which liquidity is sufficient to satisfy depositors, but the remaining is not enough to cancel all short term debt. This means that the bank will need to rollover a fraction of this debt.

Bank's maximization problem is given by the following expression:

$$\Pi \equiv \int_{0}^{\lambda+k+d-1} \left[M(1-\lambda) - (1-k-\lambda) \right] f(\beta) d\beta + \int_{\lambda+k+d-1}^{\lambda} \left[M(1-\lambda) - (d-\beta) - \frac{(1-d-k)-(\lambda-\beta)}{\theta} \right] f(\beta) d\beta - \frac{c}{2}\theta^2 - \rho k.$$

The first integral captures the case in which liquidity is enough to pay back both early withdrawals and all short term debt. This case resembles the baseline model. The second integral corresponds to the situation in which liquid assets are sufficient to satisfy deposit withdrawals, but not to pay all short term debt. In this case, the bank needs to rollover $(1-d-k)-(\lambda-\beta)$ for which it pays $\frac{1}{\theta}$. Additionally, the bank still needs to pay $(d-\beta)$ deposits at $t = 2$. The FOCs for the bank are:

[12] The interest payment for short term creditors at $t = 1$ is 1. We are assuming implicitly that in case of default at $t = 1$ due to liquidity problems, bank's remaining assets are enough to payback these creditors.

$$
\begin{aligned}
[\theta] : \theta^* =& \frac{1}{c} \int_0^{\lambda+k+d-1} \left(M(1-\lambda) - (1-k-\lambda) \right) f(\beta) d\beta + \\
& \frac{1}{c} \int_{\lambda+k+d-1}^{\lambda} \left(M(1-\lambda) - (d-\beta) \right) f(\beta) d\beta
\end{aligned}
$$

$$
\begin{aligned}
[\lambda] : & \int_0^{\lambda+k+d-1} (1-\theta M) f(\beta) d\beta + \\
& \int_{\lambda+k+d-1}^{\lambda} \left(\frac{1}{\theta} - M\theta \right) f(\beta) d\beta + \theta \left[M(1-\lambda) - (1+\lambda) - \frac{1-d-k}{\theta} \right] f(\lambda) = 0
\end{aligned}
$$

When including this alternative source of funds, the hump-shaped relationship between θ and λ prevails. Hence, increasing liquidity will have a dual effect on monitoring.

3.5 Conclusions

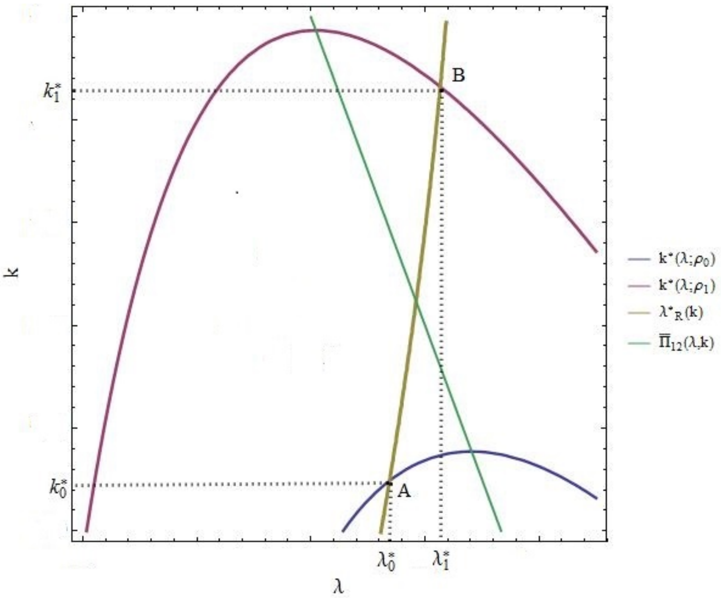
The last financial crisis showed the existence of a regulatory gap regarding liquidity standards. Regulators are turning their attention to these issues, and have started implementing liquidity requirements as a way to prevent future liquidity shortages, enhancing financial stability and reducing the need of public support to distressed institutions. The new rules in Basel III (with the LCR and the NSFR) are a clear example of this new regulatory focus.

In order to study this regulatory issue, we develop a model to analyze bank's endogenous decisions on liquidity reserves and risk taking. Liquidity has a dual effect: it reduces the risk of failing due to early withdrawals, at the cost of a lower investment in the long term asset. In this context, a regulator will set capital and liquidity requirements in order to maximize social welfare. In equilibrium, we find that the optimal capital and liquidity requirements are closely related. These regulatory tools can be complements or substitutes, depending on the shadow cost of capital. When this is relatively expensive, regulators will set lower levels of capital, leading to a complementary relationship with liquidity. On the other hand, if capital is cheaper, regulators will set higher requirements on capital, leading to a substitutability effect with liquidity.

There are important implications in terms of regulatory standards. Analyzing the regulator's problem, we find that it is socially desirable to implement liquidity requirements, since they will always be binding. But a regulator that focuses only on liquidity requirements, without explicitly accounting for its adverse consequences on monitoring, might not be able to achieve an adequate level of risk, nor to maximize social welfare. It is important for regulators to recognize the interdependence between capital and liquidity requirements.

Figures

Figure 3.1: The effect of ρ on the degree of substitution/complementarity



Note: On the vertical axis we measure capital, and on the horizontal axis liquidity. The $\bar{\Pi}_{12}$ line (green line) represents all the possible combinations between λ and k, that maximize the optimal capital (liquidity) chosen by the regulator. The yellow line $\lambda_R^*(k)$ stands for regulator's optimal liquidity choice for a given level of capital. The blue curve $k_R^*(\lambda, \rho_0)$ stands for regulator's optimal capital for any given level of liquidity. A is the optimal capital and liquidity bundle, when the cost of capital is high ($\rho_0 > \rho_1$). In this state, both regulatory tools are complementaries. If we decrease the cost of capital, regulator's optimal choice of capital as a function of liquidity $k_R^*(\lambda, \rho_1)$ shifts upward (red curve). B is the corresponding optimal bundle of capital and liquidity for a relatively lower cost of capital ($\rho_1 < \rho_0$). In this stage, these regulatory tools become substitutes.

Proofs

Proposition 1

In order to prove that $\theta_b(\lambda)$ is a hump-shaped function of λ, we will show that there is only one value for liquidity λ_b, such that $\frac{\partial\theta_b(\lambda_b)}{\partial\lambda} = 0$. Additionally, we will show that this derivative is positive for any $\lambda < \lambda_b$, while it is negative for any $\lambda > \lambda_b$. These facts characterize $\theta_b(\lambda)$ as a hump-shaped function of λ.

We start differentiating bank's monitoring effort (equation 3.2) with respect to liquidity:

$$\begin{aligned}\frac{\partial\theta_b(\lambda)}{\partial\lambda} &= \frac{f\left(\lambda\right)}{dc}\left[M(1-\lambda)-(1-\lambda-k)\right]+\frac{F\left(\lambda\right)}{c}(1-M) \Leftrightarrow \\ &= \frac{F\left(\lambda\right)}{c}\left\{\frac{\left[M(1-\lambda)-(1-\lambda-k)\right]}{d}\frac{f\left(\lambda\right)}{F\left(\lambda\right)}+1-M\right\}.\end{aligned} \tag{3.9}$$

The sign of equation (3.9) is determined by the expression inside braces. Due to the log-concavity assumption on $f(\beta)$, we know that $\frac{f(\lambda)}{F(\lambda)}$ decreases with liquidity (it approaches to infinity as $\lambda \to 0$). Then, for $\lambda \to 0$ we know that $\frac{\partial\theta_b}{\partial\lambda} > 0$, i.e. when liquidity is low, increasing λ increases monitoring.

Now, we look for the condition such that the expression inside braces in equation (3.9) is negative for high values of λ, so that $\frac{\partial\theta_b}{\partial\lambda} < 0$. Then, for higher values of λ, increasing liquidity will reduce monitoring. Let us set capital and liquidity at their corresponding extreme values in equation (3.9), i.e. $(k,\lambda) = (1-d, d)$: [13]

[13]Since equation (3.9) is increasing in k, we can assume without loss of generality that $k = 1-d$. Hence the condition will be satisfied for all possible $k \leq 1-d$.

$$\frac{\partial\theta_b(\lambda)}{\partial\lambda} = \frac{1}{c}\left\{\frac{[M(1-d)]}{d}f(d) + 1 - M\right\} < 0,$$

only if:

$$d > \frac{f(d)M}{M - 1 + Mf(d)}. \tag{3.10}$$

Note that this condition is decreasing in M, so we can always find a value for M such that it is satisfied. Then, under condition (3.10) equation (3.9) is negative as $\lambda \to d$, since $\frac{f(\lambda)}{F(\lambda)}$ decreases (due to the log-concavity assumption).

Since equation (3.9) is positive for $\lambda \to 0$, and negative for $\lambda \to d$, the fact that this is a continuous function guarantees that it equals zero at least once.

The term inside braces in equation (3.9) decreases monotonically in λ. This fact guarantees that there is only one value for $\lambda = \lambda_b$ such that $\frac{\partial\theta_b(\lambda_b)}{\partial\lambda} = 0$. This implies that for any $\lambda \geq \lambda_b$, equation (3.9) is negative. On the other hand, it will be positive on the interval $[0, \lambda_b)$. Hence, we can conclude that $\theta_b(\lambda)$ has a single peak, and therefore it is a hump-shaped function of liquidity.

Lemma 1

From equation (3.9), stated in the proof for proposition 1, we know that λ_b satisfies:

$$
\frac{\partial\theta_b(\lambda_b)}{\partial\lambda} = \frac{f(\lambda_b)}{dc}\left[M(1-\lambda_b) - (1-\lambda_b-k)\right] + \frac{F(\lambda_b)}{c}(1-M) = 0
$$
$$
\Leftrightarrow F(\lambda_b)(1-M) + \left[M(1-\lambda_b) + \lambda_b - (1-k)\right]\frac{f(\lambda_b)}{d} = 0,
$$

such that θ_b is maximized at λ_b. But this expression is equivalent to the bank's FOC with respect to λ (equation 3.3). Hence, λ_b not only maximizes bank's monitoring effort $\theta_b(\lambda)$, but also represents bank's optimal liquidity choice (the one that maximizes profits).

Lemma 2

We want to show that regulator's liquidity requirements are binding for the bank, i.e $\lambda_R^* > \lambda_b$. In order to do this, we are going to compare liquidity's FOC for the bank and regulator.

First, and for the sake of notation, let us define $\phi = M(1-\lambda) - (1-\lambda-k)$ throughout this proof. Then, we can restate bank's FOC for θ and λ (equations 3.2 and 3.3) as follows:

$$
\theta_b = \frac{F(\lambda)}{c}\phi,
$$
$$
\frac{f(\lambda)}{F(\lambda)}\phi + 1 - M = 0.
$$

Additionally, we rearrange regulator's maximization problem (equation 3.4) as follows:

$$
\Pi_R(\lambda) = \frac{F(\lambda)^2\phi^2}{2c} - \left[1 - \frac{F(\lambda)^2\phi}{c}\right](1-\lambda-k) - \rho k.
$$

Using this expression for the problem of the regulator, the corresponding

FOC with respect to λ is:

$$\begin{aligned}\frac{\partial \Pi_R(\lambda)}{\partial \lambda} =& \frac{F(\lambda)^2}{c}\phi\left[\frac{f(\lambda)}{F(\lambda)}\phi + (1-M)\right] + \left[1 - \frac{F(\lambda)^2\phi}{c}\right] \\ &+ (1-\lambda-k)\frac{F(\lambda^2)}{c}\left[2\frac{f(\lambda)\phi}{F(\lambda)} + (1-M)\right].\end{aligned}$$

Then, we need to evaluate this expression on bank's optimal liquidity (λ_b). The first term on the Right Hand Side (RHS) equals zero, since the term in brackets corresponds to bank's FOC for liquidity. By the same token, the third term on the RHS is positive. Finally, using bank's FOC for monitoring, we know that the second term on the RHS is positive as well. This means that $\frac{\partial \Pi_R(\lambda_b)}{\partial \lambda} > 0$.

This finding coupled with the fact that $\frac{\partial^2 \Pi_R(\lambda_b)}{\partial \lambda^2} < 0$, and the log-concavity assumption on $f(\beta)$, implies that $\lambda_R^* > \lambda_b$.

Lemma 3

This lemma states that regulator's optimal capital requirement is a hump-shaped function of liquidity.

Let us start rewriting regulator's FOC for capital (equation 3.5) as follows:

$$k_R^*(\lambda) = 1 - \lambda - \frac{(\rho-1)c}{F(\lambda)^2}, \tag{3.11}$$

where $k_R^*(\lambda)$ is a concave function, since $\frac{\partial^2 k^*}{\partial \lambda^2} < 0$. [14]

In order to prove that $k_R^*(\lambda)$ is a hump-shaped function of λ, we need to show the existence of a value for liquidity $\lambda < d$, such that $\frac{\partial k^*}{\partial \lambda} = 0$ (given

[14] In order to find an interior solution for capital, we restrict the values of ρ on the interval $[\underline{\rho}, \overline{\rho}]$. We set the lower bound for the cost of capital $\underline{\rho}$, such that the maximum level of capital chosen by the regulator is not higher than the natural bound for capital, i.e. $\max\limits_{\lambda} k_R^* \leq 1 - d$. On the other hand, to guarantee that the regulator has incentives to use capital $k_R^*(d) > 0$, we set the upper-bound for capital cost $\overline{\rho} < 1 + \frac{1-d}{c}$.

the concavity of $k_R^*(\lambda)$).

Using the implicit function theorem we can state that:

$$\frac{\partial k_R^*}{\partial \lambda} = -\frac{\frac{\partial^2 \Pi_R}{\partial k \partial \lambda}}{\frac{\partial^2 \Pi_R}{\partial k^2}}.$$

From the Second Order Condition (SOC) with respect to k, we know that:

$$\frac{\partial^2 \Pi_R}{\partial k^2} = -\frac{F(\lambda)^2}{c} < 0,$$

then, the sign of $\frac{\partial k_R^*}{\partial \lambda}$ will be determined by the second-order mixed derivative. Differentiating the FOC for k in equation (3.5) with respect to λ we get:

$$\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} = \frac{F(\lambda)^2}{c}\left[2\frac{f(\lambda)}{F(\lambda)}(1-\lambda-k)-1\right].$$

Note that the term in brackets will determine the direction of $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda}$, and therefore the direction of $\frac{\partial k_R^*}{\partial \lambda}$. Particularly, if the second-order mixed derivative equals zero, then $\frac{\partial k_R^*}{\partial \lambda} = 0$. Let us now define the *max curve* $\Phi(k, \lambda)$, as all the combinations between k and λ, such that $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} = 0$.

$$\Phi(k, \lambda) \equiv \left[2\frac{f(\lambda)}{F(\lambda)}(1-\lambda-k)-1\right] = 0. \tag{3.12}$$

Note that the term inside brackets decreases with capital and liquidity.

Since that k is defined in the $[0, 1-d]$ range, we look for the levels of liquidity $(\overline{\lambda}, \underline{\lambda})$ such that we lie on $\Phi(k, \lambda)$ for these extreme values of capital.

This means that, $\overline{\lambda}$ and $\underline{\lambda}$ satisfy $\Phi(0, \overline{\lambda})$ and $\Phi(1-d, \underline{\lambda})$ respectively.[15] [16]

Then, for any the combination between (k, λ) that lies above the *max curve*, we know that the term in brackets from equation (3.12) will be negative (just like $\frac{\partial k_R^*}{\partial \lambda}$). On the other hand, for any combination between (k, λ) that lies below the *max curve*, the term inside brackets will be positive (as well as $\frac{\partial k_R^*}{\partial \lambda}$).

Given that for low levels of liquidity $\frac{f(\lambda)}{F(\lambda)} \to \infty$, and using the log-concavity assumption of $f(\beta)$, from equation (3.12) we know that $\frac{\partial k_R^*}{\partial \lambda} > 0$. Then, for low values of liquidity $k_R^*(\lambda)$ must be below the curve $\Phi(k, \lambda)$.

On the other hand, we know that $k_R^*(d) > 0 \ \forall \rho \in [\underline{\rho}, \overline{\rho}]$. In particular, since $\overline{\lambda} < d$ we know that $k_R^*(\overline{\lambda}) > 0$. Then, the pair $(k_R^*(\overline{\lambda}), \overline{\lambda})$ will be above the pair $(0, (\overline{\lambda})$ that belongs to the *max curve* Φ. Therefore, as we explained before $\frac{\partial k_R^*}{\partial \lambda} < 0$.

Then, given that $k^*(\lambda)$ is a continuous function, there exist a value $\hat{\lambda}$ $\in [0, \overline{\lambda}]$ such that $\Phi(k_R^*(\hat{\lambda}), \hat{\lambda})$, so k_R^* reaches a peak at $\hat{\lambda}$. Hence, we conclude that $k_R^*(\lambda)$ is a hump-shaped function of liquidity.

Lemma 4

This lemma states that regulator's optimal liquidity requirement λ_R^*, is a hump-shaped function of capital. Rearranging equation (3.6), we know that $\lambda_R^*(k)$ must satisfy:

[15] In order to guarantee that $\overline{\lambda} \leq d$, and using equation (3.10), we assume that $d \geq Max\left[\frac{f(d)M}{M-1+Mf(d)}, 1-\frac{0.5}{f(d)}\right]$. The first term corresponds to the condition (3.10). In order to obtain the second term, we set $\overline{\lambda}$ equal to d in $\Phi(0, \underline{\lambda})$ and solve.

[16] Rearranging the *max curve*, we get $k = 1 - \lambda - \frac{F(\lambda)}{2f(\lambda)}$. This is a decreasing function of λ. Furthermore, $\overline{\lambda}$ satisfies $\frac{f(\overline{\lambda})}{F(\overline{\lambda})}(1-\overline{\lambda}) = \frac{1}{2}$ and $\underline{\lambda}$ satisfies $\frac{f(\underline{\lambda})}{F(\underline{\lambda})}(d-\underline{\lambda}) = \frac{1}{2}$, with $\overline{\lambda} > \underline{\lambda}$.

$$\frac{f(\lambda_R^*)}{F(\lambda_R^*)} = \frac{(M-1)(1-\lambda_R^*-k)+M(M(1-\lambda_R^*)-1+\lambda_R^*+k)-\dfrac{c}{F(\lambda_R^*)^2}}{(M(1-\lambda_R^*)-1+\lambda_R^*+k)(M(1-\lambda_R^*)+1-\lambda_R^*-k)}, \tag{3.13}$$

and from the implicit function theorem:

$$\frac{\partial \lambda_R^*(k)}{\partial k} = -\frac{\frac{\partial^2 \Pi_R}{\partial k \partial \lambda}}{\frac{\partial^2 \Pi_R}{\partial \lambda^2}}.$$

Then, the sign of $\frac{\partial \lambda_R^*}{\partial k}$ is driven by $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda}$, since from the SOC we know that $\frac{\partial^2 \Pi_R}{\partial \lambda^2} < 0$.

To prove this lemma, we need to show that $\lambda_R^*(k)$ intersects the curve Φ once (equation 3.12). Similar to the proof for lemma 3, whenever $\lambda_R^*(k)$ is below Φ, we know that $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} > 0$. On the other hand, if $\lambda_R^*(k)$ is above Φ, then $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} < 0$. Therefore, $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} = 0$ when $\lambda_R^*(k)$ reaches a peak and intersects Φ.

Given that M has a negative effect on the optimal liquidity ($\frac{\partial \lambda_R^*}{\partial M} < 0$), we need to set a lower and upper bound for M ($\underline{M}, \overline{M}$), such that $\lambda_R^*(0) < \overline{\lambda}$ and $\lambda_R^*(1-d) > \underline{\lambda}$. [17] [18]

The first of these previous conditions ($\lambda_R^*(0) < \overline{\lambda}$) implies that the pair $(k, \lambda) = (0, \lambda_R^*(0))$ is below the curve Φ, and therefore $\frac{\partial \lambda_R^*(0)}{\partial k} > 0$ (given the effect on the second-order mixed derivative). The second condition ($\lambda_R^*(1-d) > \underline{\lambda}$) implies that the pair $(k, \lambda) = ((1-d), \lambda_R^*(1-d))$ is above Φ, such that $\frac{\partial \lambda_R^*(1-d)}{\partial k} < 0$. Then, the continuity of $\lambda_R^*(k)$ guarantees the existence

[17]Using the implicit function theorem we know that $\frac{\partial \lambda_R^*(k)}{\partial M} = -\frac{\frac{\partial^2 \Pi_R}{\partial M \partial \lambda}}{\frac{\partial^2 \Pi_R}{\partial \lambda^2}}$. Given that $\frac{\partial^2 \Pi_R(\lambda_R^*)}{\partial \lambda^2} < 0$, the sign of this derivative is determined by $\frac{\partial^2 \Pi_R(\lambda_R^*)}{\partial M \partial \lambda} = 2M(1-\lambda_R^*)\left(\frac{f(\lambda_R^*)}{F(\lambda_R^*)}(1-\lambda_R^*)-1\right)$. From (3.13), $\frac{f(\lambda_R^*)}{F(\lambda_R^*)}(1-\lambda_R^*) < 1$. Therefore $\frac{\partial \lambda_R^*(k)}{\partial M} < 0$.

[18]Remember that $\underline{\lambda}$ and $\overline{\lambda}$ satisfy $\Phi(1-d, \underline{\lambda}) = 0$ and $\Phi(0, \overline{\lambda}) = 0$, respectively.

of a k such that $\lambda_R^*(\hat{k})$ intersects Φ at least once. Then, we show that these curves intersect only once for a capital $k = \hat{k}$, where $\lambda_R^*(\hat{k})$ reaches a peak.

In order to obtain $\underline{M}$ such that $\overline{\lambda} = \lambda_R^*(0)$, we start evaluating equation (3.13) at $k = 0$.[19] Then, $\lambda_R^*(0)$ satisfies:

$$\frac{f(\lambda_R^*)}{F(\lambda_R^*)} = \frac{1}{1-\lambda_R^*} - \frac{c}{(M(1-\lambda_R^*)-1+\lambda_R^*+k)(M(1-\lambda_R^*)+1-\lambda_R^*-k)F(\lambda_R^*)^2(1-\lambda_R^*)}$$

$$\Leftrightarrow \frac{f(\lambda_R^*)}{F(\lambda_R^*)}(1-\lambda_R^*) = 1 - \frac{c}{(M(1-\lambda_R^*)-1+\lambda_R^*+k)(M(1-\lambda_R^*)+1-\lambda_R^*-k)F(\lambda_R^*)^2}.$$

Then, using the fact that $\Phi(0,\overline{\lambda})$ leads to $\frac{f(\overline{\lambda})}{F(\overline{\lambda})}(1-\overline{\lambda}) = \frac{1}{2}$ (from equation 3.12), and replacing λ_R^* for $\overline{\lambda}$ in the previous expression, we can solve for M's lower bound:

$$\frac{1}{2} = 1 - \frac{c}{(M(1-\overline{\lambda})-1+\overline{\lambda}+k)(M(1-\overline{\lambda})+1-\overline{\lambda}-k)F(\overline{\lambda})^2} \Leftrightarrow$$

$$\underline{M} = \left(1 + \frac{2c}{F(\bar{\lambda})(1-\bar{\lambda})}\right)^{0.5}.$$

Given that $\frac{\partial \lambda_R^*}{\partial M} < 0$, we know that for all $M > \underline{M}$, $\lambda_R^*(0) < \overline{\lambda}$, and for low values of k, $\lambda_R^*(k)$ will be an increasing function of capital.

Now, we look for the $\overline{M}$ such that $\lambda_R^*(1-d) = \underline{\lambda}$. As before, we use the fact that $\Phi(1-d,\underline{\lambda})$ leads to $\frac{f(\underline{\lambda})}{F(\underline{\lambda})}(d-\underline{\lambda}) = \frac{1}{2}$ (using equation 3.12). Then, evaluating equation (3.13) at $(k,\lambda) = (1-d,\underline{\lambda})$, and using a similar procedure as for $\underline{M}$, we find the upper bound for M:

[19]For any M higher than $\underline{M}$, it is socially optimal to carry out the project.

$$\overline{M} = \left(\frac{\frac{(d-\underline{\lambda})^2}{2} + \frac{c(d-\underline{\lambda})}{F(\underline{\lambda})^2}}{(1-\underline{\lambda})(d-\underline{\lambda}) - \frac{(1-\underline{\lambda})^2}{2}} \right)^{0.5}.$$

Then, for all $M < \overline{M}$ we know that $\lambda_R^*(1-d) > \underline{\lambda}$, since $\frac{\partial \lambda_R^*}{\partial M} < 0$. This fact implies that $\lambda_R^*(k)$ will be a decreasing function of capital when $k \to (1-d)$.

Given that $\lambda_R^*(0) < \overline{\lambda}$, and $\lambda_R^*(1-d) > \underline{\lambda}$ for all $M \in (\underline{M}, \overline{M})$, we use the fact that $\lambda_R^*(k)$ is a continuous function, to prove the existence of at least one value of k such that $\lambda_R^*(k)$ intersects Φ.

Now, we will show that these curves only intersect once, i.e. the level of k for which $\lambda_R^*(k)$ intersects Φ is unique. In order to do that, let us assume that $\lambda_R^*(k)$ intersects Φ more than once, defining $\hat{k}$ as the minimum level of k such that $\lambda_R^*(\hat{k})$ intersects $\Phi(\lambda_R^*(\hat{k}), \hat{k})$. Since $\lambda_R^*(k)$ is an increasing function for low levels of capital, this curve will intersect Φ at $k = \hat{k}$ from below. If $k = \hat{k}$ is not unique, then there should be a value $\hat{\hat{k}} > \hat{k}$ such $\lambda_R^*(k)$ intersects Φ from above, which implies that $\frac{\partial k_R^*\left(\hat{\hat{k}}\right)}{\partial \lambda} < 0$. However, the sign of $\frac{\partial k_R^*}{\partial \lambda}$ is driven by $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda}$, which is zero on Φ. This fact implies that $\lambda_R^*(k)$ can not intersect Φ from above. Hence, these curves have to intersect only once at the level of capital $k = \hat{k}$.

Therefore, $\lambda_R^*(k)$ is an increasing function for any $k < \hat{k}$, it reaches a peak at $k = \hat{k}$, and it decreases for any $k > \hat{k}$. Hence, we can conclude that $\lambda_R^*(k)$ is a hump-shaped function of k.

Proposition 2

In this section, we prove that the cost of capital determines the degree of substitutability/complementarity between the optimal requirements on capital and liquidity. These tools are complements if the regulator's optimal policy given by the pair (k_R^*, λ_R^*), is below the curve Φ, and substitutes if (k_R^*, λ_R^*) lies above Φ. Note that the pair (k_R^*, λ_R^*) corresponds to the intersection between two parametric curves $(k_R^*(\lambda), \lambda)$ and $(k, \lambda_R^*(k))$. [20]

It is noteworthy the fact that the cost of capital ρ only affects $k_R^*(\lambda)$, but does not have any effect on $\lambda_R^*(k)$. For instance, a reduction in ρ produces a parallel upward shift of $k_R^*(\lambda)$, but it does not affect $\lambda_R^*(k)$. Then, as we change ρ the new equilibrium will remain on the original curve $(k, \lambda_R^*(k))$. Since this change is continuum in ρ, we show that for a value $\underline{\rho}$ regulator's optimal policy (k_R^*, λ_R^*) will be above Φ. On the other hand, for ρ_0 regulator's choice $(k_0, \lambda_R^*(k_0))$ will be below Φ. This implies that, there exist a value $\rho = \hat{\rho} \in (\underline{\rho}, \rho_0)$ such that $\lambda_R^*(k)$ and $k_R^*(\lambda)$ intersect, and this intersection occurs on the curve Φ.

First, we show that for $\rho = \underline{\rho}$, regulator's optimal policy (k_R^*, λ_R^*) is above Φ. In the proof of lemma 3, we define the lower bound of $\rho = \underline{\rho}$ such that $k_R^*(\lambda; \underline{\rho})$ intersects Φ exactly at the pair $(k, \lambda) = (1 - d, \underline{\lambda})$. This means that $k_R^*(\lambda; \underline{\rho})$ is above Φ for any $\lambda > \underline{\lambda}$. In particular, the pairs $A = (1 - d, \underline{\lambda})$ and $B = (k_R^*(d; \underline{\rho}), d)$ lie on the parametric curve $(k_R^*(\lambda; \underline{\rho}), \lambda)$, where d is the upper bound for liquidity and $k_R^*(d; \underline{\rho}) > 0$.

On the other hand, from Lemma 4 we know that $\lambda_R^*(k)$ intersects Φ at $\hat{k}$,

[20] For all the combinations (k, λ) below Φ, the second order mixed-derivative is positive, i.e. $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} > 0$. This means that increasing increasing capital and liquidity will increase welfare, i.e. both requirements are complements. On the other hand, for any pair (k, λ) above Φ, we know that $\frac{\partial^2 \Pi_R}{\partial k \partial \lambda} < 0$. Hence, increasing capital (or liquidity) should be accompanied by a decrease in liquidity (or capital). This means that the regulatory tools are substitutes.

and $\underline{\lambda} < \lambda_R^*(1-d) < \overline{\lambda}$. Then, for a level of capital $k_R^*(d;\underline{\rho})$ we know that the corresponding optimal liquidity is $\lambda_R^*(k^*(d;\underline{\rho})) < \overline{\lambda}$. In particular, the pairs $C = (1-d, \lambda_R^*(1-d))$ and $D = (k_R^*(d;\underline{\rho}), \lambda_R^*(k^*(d;\underline{\rho})))$ lie on the parametric curve $(k; \lambda_R^*(k))$.

Now, let us compare the combinations A and C. We observe that the parametric curve $(k; \lambda_R^*(k))$ is above of $(k_R^*(\lambda;\underline{\rho}), \lambda)$. Comparing the combinations B and D we observe that $(k; \lambda_R^*(k))$ is below the parametric curve $(k_R^*(\lambda;\underline{\rho}), \lambda)$. Then, the continuity of these parametric curves guarantees that they intersect above Φ, so that capital and liquidity are substitutes.[21]

Then, from lemma 4 we know that capital is low the curve $\lambda_R^*(\lambda)$ is below Φ. In particular, assume that the pair $(k_0, \lambda_R^*(k_0))$ lies below Φ. Then, it is possible to find a value of ρ_0, such that $(k^*(\lambda), \lambda)$ intersects $(k, \lambda_R^*(k))$ at $(k_0, \lambda_R^*(k))$. This implies that liquidity and capital instrument are complements. If we evaluate equation (3.11) at λ_0 (which leads to the corresponding $k_0 = k_R^*(\lambda_0)$), we can solve for ρ_0:

$$\rho_0 = \frac{(1 - \lambda_R^*(k_0) - k_0)F(\lambda_R^*(k_0))^2}{c} + 1 > 1.$$

We find that for $\underline{\rho}$ capital and liquidity are substitutes, while for ρ_0 they are complements. Since changes in ρ produce a continuous parallel shift of $k_R^*(\lambda)$, then there exist a value of $\rho = \hat{\rho} \in (\underline{\rho}, \rho_0)$ such that $(k, \lambda_R^*(k))$ and $(k_R^*(\lambda), \lambda)$ intersect on the curve Φ. This means that for $\rho < \hat{\rho}$, $(k_R^*(\lambda), \lambda)$ intersects $(k, \lambda_R^*(k))$ above Φ, while for any $\rho > \hat{\rho}$, $(k_R^*(\lambda), \lambda)$ intersects $(k, \lambda_R^*(k))$ below Φ. Then, we can conclude that the cost of capital determines the degree of substitutability/complementarity between requirements on capital and liquidity.

[21]Remember that $k_R^*(\lambda;\underline{\rho})$ is above Φ for all $\lambda > \underline{\lambda}$.

Proposition 3

In order to prove that $\theta_L(\lambda)$ is a hump-shaped function of λ, we proceed like in the proof for Proposition (1). Differentiating $\theta_L(\lambda)$ with respect to λ we obtain:

$$\frac{\partial \theta_L^*}{\partial \lambda} = \frac{1 - M + \int_\lambda^d (\rho_L - 1) f(\beta) d\beta}{c} \Leftrightarrow \frac{1 - M + (1 - F(\lambda))(\rho_L - 1)}{c},$$

Note that $\frac{\partial \theta_L^*}{\partial \lambda}$ is positive when $\lambda \to 0$, and negative when $\lambda \to d$. The monotonicity of $\frac{\partial \theta_L^*}{\partial \lambda}$ guarantees that it reaches the value zero once. Hence, $\theta_L(\lambda)$ is a hump-shaped function.

In order to prove that monitoring effort will be higher if there is a LoLR, we analyze the difference $\theta_L(\lambda) - \theta_b(\lambda)$:

$$\theta_L(\lambda) - \theta_b(\lambda) = \frac{(1 - F(\lambda)\left(M(1-\lambda) - 1 + \lambda + k)\right) - \int_\lambda^d (\rho_L - 1)(\beta - \lambda) f(\beta) d\beta}{c} \Leftrightarrow$$
$$= \frac{\int_\lambda^d M(1-\lambda) - 1 + \lambda + k) - (\rho_L - 1)(\beta - \lambda) f(\beta) d\beta}{c} > 0,$$

given that $M < \rho_L < \frac{M}{d}$. Since the bank chooses the level of liquidity that maximizes its level of monitoring, then it is straightforward that a bank that receives support from a LoLR will choose a higher level of monitoring.

Proposition 4

This proposition states that, if there is a regulator acting as a LoLR, increasing liquidity will lead to a lower capital requirement. Let us start analyzing the FOC for capital:

$$[k]: \;\; k^*(\lambda) = 1 - \lambda - c(\rho - 1) + \rho_L \int_\lambda^d (\beta - \lambda) f(\beta) d\beta.$$

If we differentiate this expression with respect to liquidity:

$$\frac{\partial k^*(\lambda)}{\partial \lambda} = -1 - \rho_L \int_\lambda^d f(\beta) d\beta < 0.$$

Then, these regulatory tools are substitutes.

Lemma 5

In order to show that bank's liquidity choice is increasing in L (representing the liquidation cost for the long term asset), we use the implicit function theorem and find that:

$$\frac{\partial \lambda_{FS}}{\partial L} = \left[F(\overline{\beta} - F(\lambda_{FS})\right] M + f(\overline{\beta}) \frac{M(L-1)}{ML-1} > 0,$$

which is what we wanted to show.

Proposition 5

Similar to previous cases, in order to prove that liquidity maximizes monitoring effort (in the presence of a systemic shock and uncorrelated loans) one can simply compare the bank's FOCs with respect to θ and λ. Additionally, comparing the monitoring effort with systemic shocks with the monitoring in the baseline scenario (θ_{SR} and θ_b) it is straightforward that $\theta_{SR} < \theta_b$.

In order to show that θ_{SR} is a hump-shaped function, we analyze the derivative of monitoring with respect to liquidity:

$$\frac{\partial\theta_{SR}}{\partial\lambda} = \frac{\int_{\underline{\gamma}}^{2}\left\{f(\lambda)\left[\gamma M(1-\lambda)-(1-k-\lambda)\right]+F(\lambda)(1-M\gamma)g(\gamma)d\gamma\right\}}{c} \Leftrightarrow$$
$$\frac{\int_{\underline{\gamma}}^{2}\left\{\frac{f(\lambda)}{F(\lambda)}\left[\gamma M(1-\lambda)-(1-k-\lambda)\right]g(\gamma)d\gamma+\int_{\underline{\gamma}}^{2}(1-M\gamma)\right\}g(\gamma)d\gamma}{c}$$

The log-concavity assumption implies that for low levels of λ this expression is positive (since $\frac{f(\lambda)}{F(\lambda)}$ is large). On the other hand, for higher levels of liquidity (when $\lambda \to d$) the condition 3.10 guarantees that the above expression becomes negative. Hence, because of the continuity of the function, we can assert that θ_{SR} is a hump-shaped function of λ.

Finally, in order to show that liquidity is higher in the presence of a systemic shock (compared to the baseline model), let us restate the FOC with respect to liquidity as follows:

$$[\lambda] : f(\lambda)\left[E(\gamma)M(1-\lambda)-(1-k-\lambda)\right]+F(\lambda)(1-ME(\gamma)) = 0$$

Note that this expression resembles the one from the baseline model (equation 3.3). The only difference is that the long term project's return M is multiplied by $E(\gamma)$, which equals one.

Bibliography

Acharya, V., Drechsler, I., and Schnabl, P. (2014). A pyrrhic victory? bank bailouts and sovereign credit risk. *The Journal of Finance*, 69(6):2689–2739.

Acharya, V. V. and Rajan, R. G. (2013). Sovereign debt, government myopia, and the financial sector. *Review of Financial Studies*, 26(6):1526–1560.

Acharya, V. V. and Steffen, S. (2015). The greatest carry trade ever? understanding eurozone bank risks. *Journal of Financial Economics*, 115(2):215–236.

Afonso, A., Furceri, D., and Gomes, P. (2012). Sovereign credit ratings and financial markets linkages: application to european data. *Journal of International Money and Finance*, 31(3):606–638.

Ait-Sahalia, Y., Andritzky, J., Jobst, A., Nowak, S., and Tamirisa, N. (2012). Market response to policy initiatives during the global financial crisis. *Journal of International Economics*, 87(1):162–177.

Allen, F., Carletti, E., and Leonello, A. (2011a). Deposit insurance and risk taking. *Oxford Review of Economic Policy*, 27(3):464–478.

Allen, F., Carletti, E., and Marquez, R. (2011b). Credit market competition and capital regulation. *Review of Financial Studies*, 24(4):983–1018.

Baier, S. L., Clance, M., and Dwyer Jr, G. (2012). Banking crises and economic freedom. *Federal Reserve Bank of Atlanta Working Paper*.

Bar-Isaac, H. and Shapiro, J. (2013). Ratings quality over the business cycle. *Journal of Financial Economics*, 108(1):62–78.

Beltratti, A. and Stulz, R. M. (2015). Bank sovereign bond holdings, sovereign shock spillovers, and moral hazard during the european crisis. *National Bureau of Economic Research*, No. w21150.

Bernoth, K., Von Hagen, J., and Schuknecht, L. (2012). Sovereign risk premiums in the european government bond market. *Journal of International Money and Finance*, 31(5):975–995.

Bertay, A. C., Demirgüç-Kunt, A., and Huizinga, H. (2013). Do we need big banks? evidence on performance, strategy and market discipline. *Journal of Financial Intermediation*, 22(4):532–558.

Billett, M. T., Garfinkel, J. A., and O'Neal, E. S. (1998). The cost of market versus regulatory discipline in banking. *Journal of Financial Economics*, 48(3):333–358.

Bushman, R. M. and Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of banks risk-taking. *Journal of Accounting and Economics*, 54(1):1–18.

Calomiris, C. W., Heider, F., and Hoerova, M. (2015). A theory of bank liquidity requirements. *Columbia Business School Research Paper*, (14-39).

Calomiris, C. W. and Kahn, C. M. (1991). The role of demandable debt in structuring optimal banking arrangements. *The American Economic Review*, 81:497–513.

De Nicoló, G., Gamba, A., and Lucchetta, M. (2014). Microprudential regulation in a dynamic model of banking. *Review of Financial Studies*, 27(7):2097–2138.

DellAriccia, G. and Marquez, R. (2006). Competition among regulators and credit market integration. *Journal of Financial Economics*, 79(2):401–430.

Demirgüç-Kunt, A. and Huizinga, H. (2004). Market discipline and deposit insurance. *Journal of Monetary Economics*, 51(2):375–399.

Demirgüç-Kunt, A. and Huizinga, H. (2013). Are banks too big to fail or too big to save? international evidence from equity prices and cds spreads. *Journal of Banking & Finance*, 37(3):875–894.

Dewatripont, M. (2014). European banking: Bailout, bail-in and state aid control. *International Journal of Industrial Organization*, 34:37–43.

Diamond, D. W. and Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, pages 401–419.

Dieckmann, S. and Plank, T. (2012). Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance*, 16(4):903–934.

Flannery, M. J. and Sorescu, S. M. (1996). Evidence of bank market discipline in subordinated debenture yields: 1983–1991. *The Journal of Finance*, 51(4):1347–1377.

Freixas, X., Martin, A., and Skeie, D. (2011). Bank liquidity, interbank markets, and monetary policy. *Review of Financial Studies*, 24(8):2656–2692.

Gennaioli, N., Martin, A., and Rossi, S. (2014). Sovereign default, domestic banks, and financial institutions. *The Journal of Finance*, 69(2):819–866.

Gorton, G. and Santomero, A. M. (1990). Market discipline and bank subordinated debt: Note. *Journal of Money, Credit and Banking*, 22(1):119–128.

Huizinga, H. and Demirgüç-Kunt, A. (2011). Do we need big banks? *VOX*, March 18, 2011. Available: `http://www.voxeu.org/article/do-we-need-big-banks`.

Kothari, S. and Warner, J. B. (2007). Econometrics of Event Studies. Handbook of Corporate Finance: Empirical Corporate Finance. B. Espen Eckbo.

Lane, P. R. (2012). The european sovereign debt crisis. *The Journal of Economic Perspectives*, 26(3):49–67.

Leonello, A. (2015). Government guarantees and the two-way feedback between banking and sovereign debt crises (mimeo).

Martinez-Peria, M. S. and Schmukler, S. L. (2001). Do depositors punish banks for bad behavior? market discipline, deposit insurance, and banking crises. *The Journal of Finance*, 56(3):1029–1051.

Millstein, J. (2011). Europe's largest banks have become too big to save. *Financial Times*, November 14, 2011.

Moody's Investors Service (2013). Rating Methodology - Global Banks. May 31, 2013. Available: `https://www.moodys.com/researchdocumentcontentpage.aspx?docid=PBC_154255`.

Morgan, D. P. (2002). Rating banks: Risk and uncertainty in an opaque industry. *American Economic Review*, 92(4):874–888.

Morgan, D. P. and Stiroh, K. J. (2001). Market discipline of banks: The asset test. *Journal of Financial Services Research*, 20(2-3):195–208.

Nier, E. and Baumann, U. (2006). Market discipline, disclosure and moral hazard in banking. *Journal of Financial Intermediation*, 15(3):332–361.

O'Hara, M. and Shaw, W. (1990). Deposit insurance and wealth effects: the value of being too big to fail. *The Journal of Finance*, 45(5):1587–1600.

Ongena, S., Smith, D. C., and Michalsen, D. (2003). Firms and their distressed banks: lessons from the norwegian banking crisis. *Journal of Financial Economics*, 67(1):81–112.

Penas, M. F. and Unal, H. (2004). Gains in bank mergers: Evidence from the bond markets. *Journal of Financial Economics*, 74(1):149–179.

Repullo, R. (2004). Capital requirements, market power, and risk-taking in banking. *Journal of financial Intermediation*, 13(2):156–182.

Repullo, R. (2005). Liquidity, risk-taking and the lender of last resort. *International Journal of Central Banking*, 1:47–80.

Rime, B. (2005). Do too-big-to-fail expectations boost large banks issuer ratings. *Swiss National Banks, Systemic Stability Section: Working Paper (May 9).*

Roberts, M. and Whited, T. (2012). Endogeneity in empirical corporate finance. *Simon School Working Paper No. FR 11-29.*

Stein, J. C. (2013). Liquidity regulation and central banking. In *Speech at the "Finding the Right Balance" 2013 Credit Markets Symposium sponsored by the Federal Reserve Bank of Richmond, Charlotte, North Carolina.*

Vives, X. (2014). Strategic complementarity, fragility, and regulation. *Review of Financial Studies*, 27(12):3547–3592.

Walther, A. (2015). Jointly optimal regulation of bank capital and liquidity. *Journal of Money, Credit, and Banking, forthcoming.*

Zaghini, A. (2014). Bank bonds: size, systemic relevance and the sovereign. *International Finance*, 17(2):161–184.